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Novel methodology for resilience assessment of critical infrastructure considering the interdependencies: A case study in water, transportation and electricity sector

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ABSTRACT

Critical Infrastructures (CI) are vital for societal and economic stability, yet their resilience against disasters remains inadequately understood with the increasing interdependencies among the CIs. A better understanding of these interdependencies and the dynamic nature of CI functionalities is crucial for advancing disaster resilience assessment within engineering systems. This paper introduces a novel approach using a Dynamic Bayesian Network (DBN) to assess resilience in interdependent CI systems. The DBN method enables a probabilistic evaluation of system resilience by incorporating interdependencies and capturing the temporal dynamics of system capacities. This approach offers a more detailed perspective on resilience by modelling system functionality using expected values of different functionality states over time. Using a case study in Sri Lankan electricity, water distribution, and road infrastructure sectors and 34 experts, this study examines the complex network of CIs. It demonstrates the applicability of the proposed methodology. P-values of the Chi-Square test performed between the variation of model-predicted resilience and expert assessments are significantly less than 0.05, confirming the model's validity. Additionally, this study explores the expansion of the methodology for resilience assessment under multiple hazards, emphasizing its real-world effectiveness. The findings highlight the efficacy of the proposed methodology and its potential to assist asset managers, owners, and decision-makers in informed resilience planning and optimization strategies. This comprehensive approach fills critical gaps in existing methodologies, offering a robust framework for assessing CI resilience in a dynamic and systematic nature.

1. Introduction

The built environment has undergone rapid technological development in recent years, leading to a gradual increase in its

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complexity [1,2]. Technological advancements have also significantly increased human interaction with the built environment [3–6]. Critical Infrastructures (CIs) play a vital role within this environment. Broadly defined, CIs encompass assets, physical and virtual infrastructure, networks, or processes that are essential for the well-being and proper functioning of society or communities [1,2,7]. Rather than operating in isolation, CIs function as interconnected systems due to their interdependencies, which are intrinsic to CI systems. Under normal operational conditions, these interdependencies typically enhance the reliability and efficiency of infrastructure services [1,8,9]. However, during significant disruptions, these interdependencies can lead to cascading failures and delays in restoration, thereby introducing additional vulnerabilities and complexities [8,10–16]. Such failures are inherently unpredictable, specially under uncertain operational circumstances where unexpected disruptions may arise randomly. These interruptions can result from hazards or failures in system components, including natural disasters, human-made disasters, and unforeseen failure modes [1,6,17–20].

Lessons learned from recent disaster events and the recognition of unknown hazards have shifted the focus of scholars from studies on CI protection to the concept of resilience [18,21–25]. Holling [26] introduced the concept of resilience in ecology, which has been expanded and adopted across various fields [23,25,27–29]. Resilience refers to a system's ability to resist, absorb, accommodate, adapt, transform, and recover from a hazard's effects efficiently and in a timely manner. This includes safeguarding and restoring its fundamental structures and functions through effective risk management [30–32]. Given the challenges posed by unprecedented disruptions, designing resilient CI systems has become critical and complex task [1,33–37]. While redundancy is often used to enhance system resilience, it is frequently impractical for complex systems due to the high costs associated with such measures [16,25,32]. In this context, resilience assessment has emerged as a valuable tool to support decision-making in the planning and design of CI systems. Unlike traditional risk assessment, resilience assessment is better suited for addressing the complexities of CI systems facing uncertain disruptions. It places greater emphasis on unpredictable hazards and the cascading effects of failures following a disruption [16,20,25,32,38,39].

In recent years, the study of CI resilience has gained increasing attention among scholars [1,33,40,41]. The existing literature has expanded the scope of resilience assessment by presenting various methodologies for evaluating CI systems. These methodologies are generally classified as qualitative, semi-quantitative, and quantitative approaches [21,23,25,42–44]. Additionally, several studies employ diverse modeling techniques for CI resilience assessment, leveraging simulation paradigms and decision-making procedures [42,45–47].

These modeling and simulation methodologies encompass a wide range of techniques. For instance, Ouyang et al., [42] classified modeling approaches into six main categories: empirical approaches, agent-based approaches, system dynamics-based approaches, network-based approaches, economic-based approaches, and others. Similarly, Sun et al., [45] categorized these modeling techniques into three primary groups: dependency tables, interaction rules, and data-driven approaches. Standard methodologies include agent-based modeling, system dynamics, network theory, continuous time-step simulation (CS), discrete time-step simulation (DS), Monte Carlo simulation (MC), decision trees (DT), Geographic Information Systems (GIS), event monitoring or real-time records (RTR), and machine learning [21,42,43,45,47]. Various modeling techniques for resilience assessment of CIs have been systematically compared across multiple studies (See Table A 1 in Appendix A). Descriptive approaches, such as descriptive tables and survey-based matrices, are intuitive and straightforward to implement but rely heavily on subjective inputs and lack dynamic or probabilistic capabilities. Network models effectively capture physical interdependence but require detailed knowledge of network topologies and are computationally expensive. Input-output and computable general equilibrium models assess economic cascading impacts but are limited to economic effects and do not account for redundancy representation. Simulation-based approaches, such as discrete event simulation, agent-based models, and system dynamics, provide dynamic cause-and-effect analyses but are computationally intensive and require extensive expert input. In contrast, Bayesian Networks (BNs), particularly Dynamic Bayesian Networks (DBNs), are noteworthy for their ability to model resilience both dynamically and probabilistically. DBNs manage significant uncertainties by integrating data from various sources such as simulations, measurements, and expert judgments; representing interdependencies using directed graphs and conditional probabilities, and modeling evolving system states over time. Unlike static or deterministic methods, DBNs allow real-time updates, capture cascading effects, and provide comprehensive assessments by combining physical, operational, and functional interdependencies into a unified framework. Although machine learning models excel in processing large datasets, they lack the interpretability and physical insights crucial for resilience assessment. DBNs emerge as the most suitable choice for resilience modeling due to their flexibility, probabilistic nature, and ability to dynamically evaluate resilience trajectories while incorporating complex interdependencies.

Most studies assess resilience by examining the impact of disruptions on system functionality, typically focusing on functional loss. The resilience of a system is contingent upon its possession of four distinct capacities: Anticipation, Absorption, Adaptation, and Restorative capacity [48,49]. These capacities play a fundamental role in shaping the functionality states of the system [25,50,51]. In this study, the state of system functionality emerges as a pivotal determinant of system resilience. These four capacities can be comprehensively contextualized by delineating the operational dimensions of system functionality. Furthermore, the integration of these capacities with disruptions constitutes a central tenet for evaluating system functionality. Anticipation capacity entails the ability to foresee and prepare for potential disruptions or failures that may interrupt system functioning. Its significance lies in its facilitation of preparedness and proactive measures aimed at risk mitigation [25,28,48]. Conversely, absorption pertains to the system's capability to withstand, absorb, and endure disruptions. Upon the occurrence of a disruption, the system's capacity to absorb enables it to prepare and adapt independently to reduce the impact of disruptions, thereby minimizing their resultant consequences [3,52,53]. Additionally, adaptation capacity is a pivotal and indispensable aspect within the context of resilience when considering CI systems. It encapsulates the inherent capability of a CI system to respond flexibly and adeptly to dynamic and evolving conditions, as well as emerging threats that may pose risks to its functionality and integrity [23,24,54,55]. Restorative capacity pertains to the system's ability to integrate external interventions aimed at remedying the damage incurred by disruptions and facilitating its transition to a redefined state [21,23,24,54]. Acknowledging that this new state need not precisely mirror the pre-disruption condition is essential. The functionality of this new system state may exceed or fail to meet that observed before the disruptions, but it remains within an acceptable range to meet operational requirements [25,50,51].

Enhancing system resilience involves reducing functional loss and increasing the capacity for recovery in the face of unforeseen disruptions [21,23,25,42,56]. An overview of several studies that have developed resilience assessment models for CIs considering interdependencies is provided in Table A 2 (See Appendix A). Ouyang [57] introduced a methodology for evaluating the resilience of interdependent infrastructure systems. This approach incorporated unidirectional interdependencies and extends an existing resilience assessment framework for single systems to encompass interdependent systems. The primary focus is on modeling and analysing the

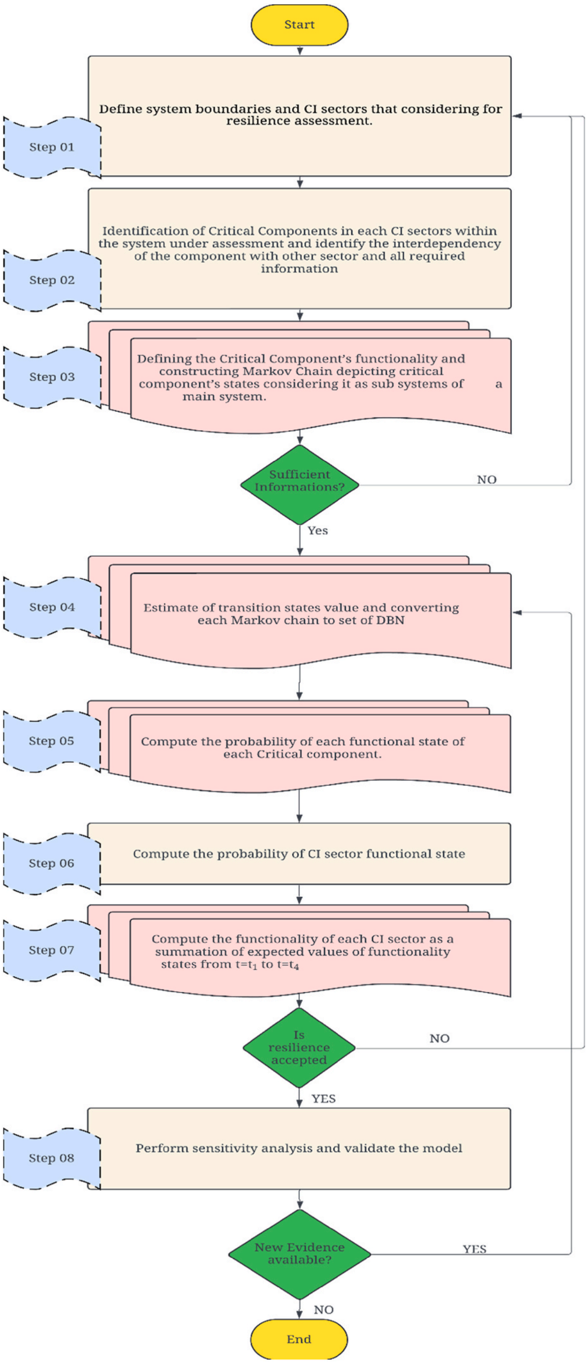


Fig. 1. The proposed methodology for resilience assessment of the CIs under disaster event.

contributions of resilience during the joint restoration processes of interconnected systems. Pederson et al. [58], and Goldbeck et al. [59], have further explored methodologies for quantifying interdependencies and their impact on resilience during disruptions. These studies highlight the value of capturing cascading effects and functional relationships in interconnected systems. Furthermore, Cai et al., Nan and Sansavini, and Kammouh et al. [60–63], have demonstrated the applicability of DBNs for modeling multi-sector interconnected networks and dynamic states of resilience. However, while these methodologies mark significant progress, gaps remain in their ability to integrate diverse interdependencies (e.g., operational, functional, and structural), specially the effect of one infrastructure's capacity affects the other infrastructure's functionality and account for multi-hazard scenarios across the lifecycle of CI systems [57,59–61]. Many existing approaches, including DBN applications, focus narrowly on single-system evaluations or simplified network configurations, leaving room for comprehensive multi-sector assessments under dynamic and uncertain conditions [21,23,25,34,42]. Additionally, during disruptions, system states undergo dynamic changes, necessitating the consideration of transitions between these states when assessing resilience [1,9,64]. On the other hand, CI systems will be impacted by multiple hazard types during their life cycle. Unfortunately, many current resilience assessment methodologies overlook these dynamic aspects and multiple hazard types, highlighting the need for more comprehensive approaches for evaluating resilience of interconnected CI systems [1,9,16,65,66].

In the current landscape of CI resilience assessment, considerable potential exists for further advancements beyond the state-of-the-art. Therefore, this study builds upon and extends existing work by proposing a novel DBN-based methodology explicitly designed to address these limitations. Unlike traditional DBN applications, the proposed framework integrates multi-sector interdependencies at the component level while dynamically accounting for transitions between functionality states. This approach surpasses static models by incorporating probabilistic evaluations that adapt to evolving system states and external disruptions in real time. A case study involving the water distribution system, road infrastructure, and electricity infrastructure was conducted to demonstrate the applicability and validity of the proposed methodology. The proposed approach aims to provide a more comprehensive and detailed understanding of CI resilience by considering both infrastructure interdependence and the evolving nature of resilience over time.

2. Significance of the study

CIs operate as interconnected systems rather than isolated entities. These interdependencies increase the risk of cascading failures triggered by primary system malfunctions, resulting in increased vulnerability and delays in restoration efforts. In this evolving context, resilience assessment has emerged as a critical tool for supporting decision-making in CI system planning and design. However, existing resilience assessment methodologies often fall short of capturing the systemic nature and dynamic behavior of interconnected CI systems. This study aims to address these gaps by introducing a novel methodology for CI resilience assessment. Utilizing a DBN-based approach, the proposed methodology offers a dynamic and probabilistic assessment of resilience, accounting for both the interconnected nature of CIs and the evolving dynamics of resilience over time. Additionally, a new metric based on the expected value of functionality states is introduced to evaluate system resilience comprehensively. A case study on the water distribution system, road infrastructure, and electricity infrastructure in Sri Lanka is presented to demonstrate the applicability and validity of the proposed methodology. The findings underscore the potential of the proposed approach to offer a more detailed understanding of CI resilience, highlighting its relevance and contribution to advancing resilience assessment methodologies in the context of interconnected and dynamic CI systems.

3. Proposed methodology for resilience assessment

This section introduces a methodology for evaluating the resilience of CI systems during disaster events, considering the dynamic nature and interdependencies among CIs. Unlike conventional methods that typically address only a single type of infrastructure, this approach integrates interdependencies, offering a more comprehensive evaluation. The proposed methodology consists of eight steps to assess the resilience of the CI system, taking into account the interdependencies during a disaster, as depicted in Fig. 1. The proposed methodology utilizes DBN for modeling the CI system. DBN can represent probabilistic relationships between causes and effects dynamically, through nodes and directed lines, enabling both predictive and evaluative examinations [67–72]. More technical details

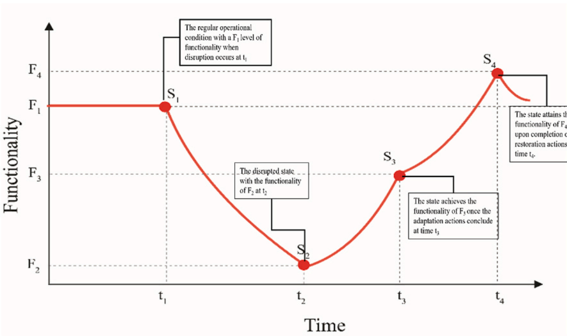


Fig. 2. Functionality curve of an infrastructure (Adopted from Refs. [25,51,78,81]).

of the DBN are discussed in Appendix B. Significantly, the evaluation can integrate observed evidence to simulate the real-time condition of a system.

Therefore, any evidence provided at any moment permits the revision of probabilities for all points within the network's arrangement. DBN models have gained extensive use in risk assessment in recent years, owing to their capacity to blend multiple states and include a temporal aspect [67–76].

Furthermore, the proposed methodology incorporates the concept of functionality (F) in its definition of resilience. After disruptions, a system may malfunction or be in a weakened state, both of which are considered "low functionality". Upon restoration to its typical operational state, it achieves a status of "high functionality". Therefore, the functionality of the system has been used to measure resilience in previous studies [25,77–80]. The functionality curve offers a graphical representation of the system's functionality, illustrating how its functionality evolves in response to external disturbances or disruptions, as depicted in Fig. 2. Accordingly, any system is assumed to operate in a finite set of functional states denoted by $s = \{s_1, s_2, ..s_i, s_{i+1}, \ldots, s_n\}$, where s_i denotes the mutually exclusive state of the system at any point in time and n is the finite number of possible states. The system's functionality when operating in the state s_i is denoted by f_i. The occurrence of system state s_i at time point t is defined by the discrete probability distribution $P(S_i)^t$.

Furthermore, if we assume the time period from the disruption occurrence t_1 until when the system achieves a new stable state (s_n) can be discretised to m number of small Δt time bins. Then the system functionality is given by Equation (1).

$$\textit{System functionality during the time of disruption} = \sum_{t=t1}^{t=t1+m\Delta t} \sum_{i=1}^{n} F_i * P(S_i)^t \tag{1}$$

t = discrete time bins.

F_i = Expected Functionality level for ith state of system.

S = State of the system.

i = System state number.

Assuming the disruption occurs at t_1, the system transitions from state S_1 to S_2, accompanied by a substantial decrease in functionality from F_1 to F_2 following the disruptive event. Subsequently, the system initiates adaptation mechanisms, improving functionality to F_3 as it adapts and undergoes repairs. Following restorative actions helps the system move from a disrupted condition to a new stable state (S_4) with the desired functionality (F_4) depending on external maintenance interventions. This cycle initiates a new state of S_4, enriched with anticipation capabilities derived from the lessons gained from the preceding disruption. Systems endowed with increased anticipation abilities typically exhibit swifter recovery rates. The system functionality can be quantified in terms of expected functionality value at a given time, as depicted in Equation (1). As the present study utilizes the functionality terms in the resilience definition, the system's functionality is defined as the summation of the expected value of the system's states as shown in Equation (1). In Equation (1), the duration from the moment of disruption (t_1 in Fig. 2) to the time when the infrastructure is fully recovered (t_4 in Fig. 2) is considered as the 'time of disruption'. This equation captures the dynamic nature of system functionality, accounting for changes in state probabilities over time and their overall impact on system. This definition of functionality introduces a new approach to resilience assessment by incorporating dynamic and probabilistic characteristics. It is important to highlight that users may need to specify the functionality level (F_i) for various system states. It should be noted that F_i represents the expected percentage of available functionality of a system at a given state. The following eight steps outline the proposed methodology.

- **Step 1: Define system boundaries and CI sectors that are considered for resilience assessment:** In this step, the system boundaries are defined, highlighting the CI sectors considered in the study. For instance, this case study examines three CI systems: electricity, water distribution, and road infrastructure. Additionally, more information related to each CI sector, such as assets and the main services provided by each sector is obtained. The definition of the functionality of each CI sector should be established at this stage. This can be accomplished through a range of sources, including industry insights, operational conditions, or the expert judgment from decision-makers.
- **Step 2: Identification of Critical Components in each CI sector within the system under assessment and identify the interdependency of the component with other sectors and all required information:** Step two of the proposed methodology involves identifying the critical components within each CI sector and the interdependencies of these components with other CI sectors. A critical component is defined as any part, subsystem, or infrastructure facility that is essential for maintaining the critical service provided by a CI sector. It should be noted that zero functionality of any critical component would result in zero functionality of the services delivered by the corresponding CI sector. Additionally, identifying interdependencies between critical services is necessary at this stage. Expert judgment can be used to identify critical components and interdependencies.
- **Step 3: Defining the Critical Component's functionality and constructing a Markov Chain depicting the critical component's states, considering it as sub-systems of a main system:** In this step, the functionality state for each critical component is defined. As shown in Fig. 2, four functionality states (S_1, S_2, S_3 and S_4) are used to define the functionality states. Then, a Markov chain representing the component's functionality states is developed. The transition rates between the states are established according to the four capacities of the system: Anticipation, Absorption, Adaptation, and Restoration. Additionally, the primary factors influencing the system's capacities are impacted by both external factors and the system itself. This study establishes the influencing factors that contribute to the main capacities, building upon previous research conducted by the same scholars [55]. In the related study, the authors developed an indicator framework based on these capacities, depicted in Fig. 3, which is utilized in this research.

- **Step 4: Estimate the transition probabilities and convert each Markov chain to a set of DBNs:** After defining the functionality state of the critical components, the subsequent step is to estimate the transition states and translate the individual Markov chains into DBNs. Fig. 4 depicts the transformation of a Markov chain model into a DBN, illustrating the transition between four functional states and improving comprehension of the process. In Fig. 4 (a), the parameters λ, μ, α, and δ represent the transition probabilities associated with the system's capacities: absorption, adaptation, restoration, and anticipation. Fig. 4(b) showcases the DBN model, that illustrates how the system's functional state evolves, influenced by nodes representing resilience attributes. The ' Functionality State' node in Fig. 4(b) encompasses states S_1, S_2, S_3, and S_4, which are influenced by the resilience capacities. The transition rates for each state are transformed into the conditional probabilities of the ' Functionality State' node, considering the resilience indicators. The transition probabilities of system's functionality states of the Markov chain are illustrated in Table 1.
- **Step 5: Compute the probability of each functional state of each Critical component:** In this step, the probability of each functional state for every critical component is calculated at each discrete time interval. The DBN model developed in the previous step enables dynamic probability assessment. By employing forward and backward propagation analysis within the DBN, probabilities can be determined, allowing decision-makers to revise the model based on the most recent evidence and adjust the system according to current conditions in real-time. The DBN structure for system resilience includes six nodes: a child node indicating the functionality state, and others representing four capacities and one disruption. The probabilities of the individual states (S_1, S_2, S_3, and S_4 as depicted in Fig. 2) are computed to quantify functionality and thereby resilience. The 'Functionality state' node encompasses four distinct states aligning with those in the Markov chain depicted in Fig. 4. The transition rates listed in Table 1 for the Markov chain are transformed into conditional probabilities. To represent the variation of the functionality state of a system over time, a temporal arc connects the 'Functionality state' node from the previous time step, *t-1*, to the subsequent time step, *t*. In this study, the nodes for the four capacities are assumed to have two states, high and low, indicating whether the system's capacities are 'High' or 'Low.' These dynamic processes influence system functionality. Temporal arcs connect the nodes 'anticipation,' 'absorption,' 'adaptation,' and 'restoration' to the 'state of functionality' node. Additionally, it is presumed that the 'disruption' node possesses two states: 'yes' and 'no,' denoting the occurrence or non-occurrence of a disruption. External disruptions may occur at any point during operation. For modeling purposes, it is assumed that a disruption occurs at the initial time step ($t = 0$), and the disruption state at this time is set to 'yes'. Fig. 5 illustrates the breakdown of the DBN and the evolving connections between nodes across distinct time intervals. These intervals, shown from left to right, represent the states at $t-1$ and *t*, respectively. The shift in system functionality is influenced by the current state's disruption, resilience attributes, and the previous state's system functionality. It's important to highlight that resilience, as a built-in characteristic of an engineered system (excluding human elements), remains unaffected by extrinsic influences such as disruptions. However, if an external influence impacts system functionality, it will consequently affect resilience.
- **Step 6: Compute the probability of CI sector functional state:** During this stage, the probability distribution of functionality state for a given discrete time bucket within the CI sector is determined as follows. Let $S_r(t)$ be the functional state of the critical

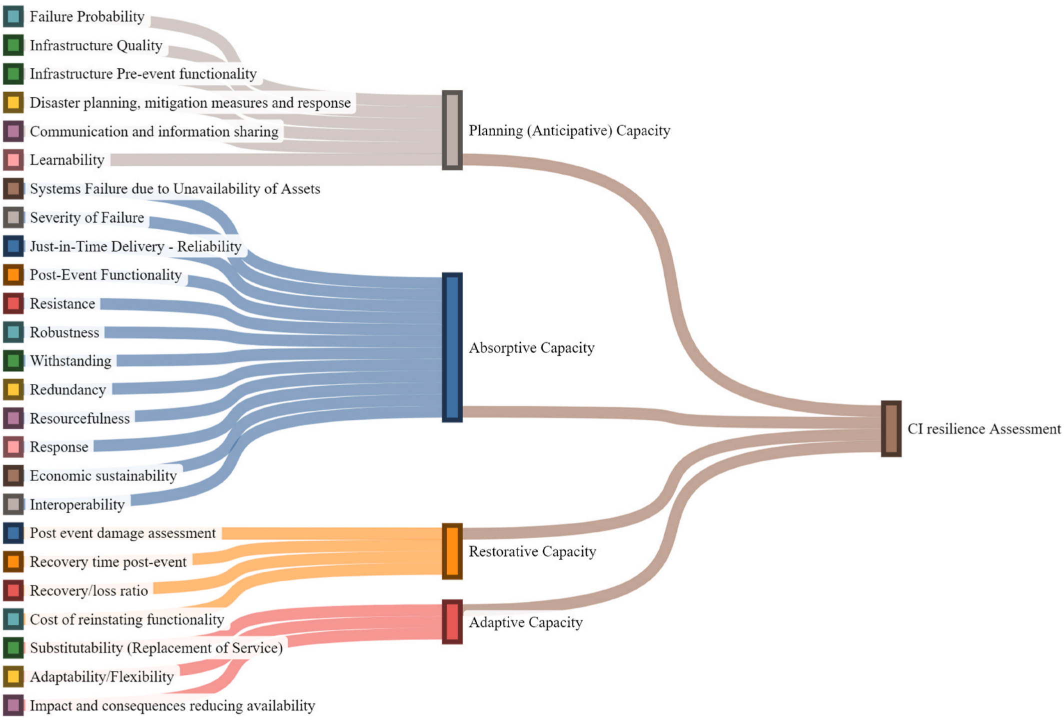


Fig. 3. Indicator framework for determining the four main capacities (Adopted from Ref. [55]).

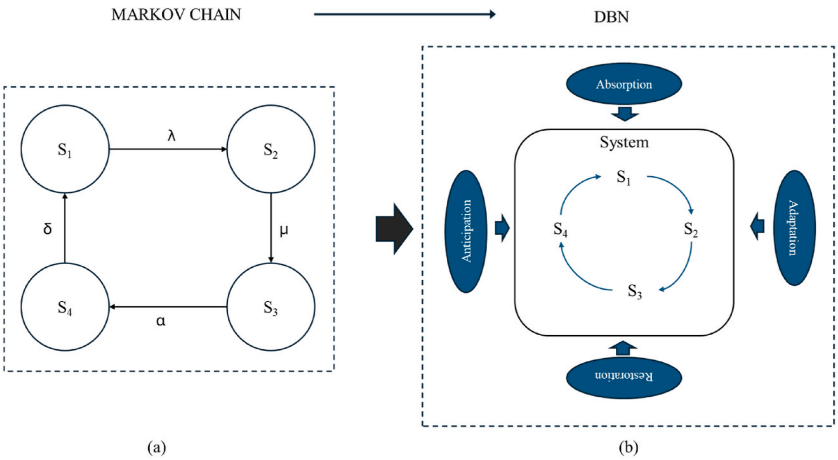


Fig. 4. Transformation of Markov chain to a DBN (Adopted from: [51]).

Table 1
Transition probabilities for the system's functionality states of the Markov chain.

Transition probability	S_1	S_2	S_3	S_4
S_1	1-λ	λ	0	0
S_2	0	1- μ	μ	0
S_3	0	0	1-α	α
S_4	δ	0	0	1-δ

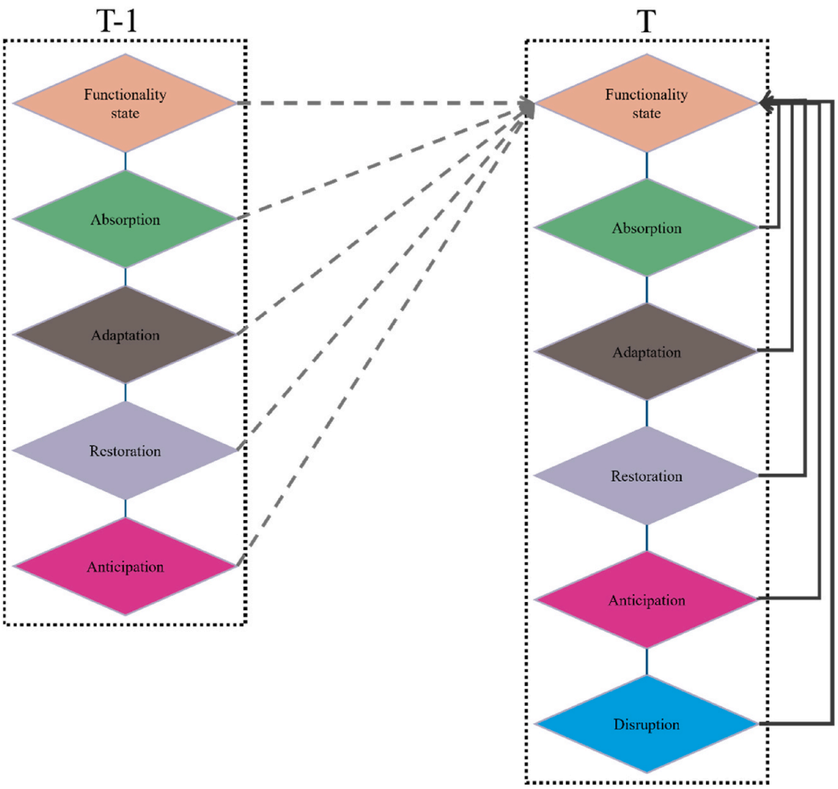


Fig. 5. DBN nodes at discrete time slices (dashes arcs represent temporal links) (Adopted from: [51]).

component C_r where $S_r(t) \in \{s_{1r}, s_{2r}, \ldots \ldots, s_{ir}, \ldots s_{nr}\}$ and $r = 1,2,3 \ldots, k$ at a given time point t. k is the number of critical components in the corresponding CI sector.

Then, at time t the states of all the critical components can expressed as: $S(t) = \{S_1(t), S_2(t) \ldots S_k(t)\}$. The corresponding set of functional levels of each critical component is given by: $F(t) = \{F_1(t), F_2(t) \ldots F_k(t)\}$, *where* $\boldsymbol{F_r}(\boldsymbol{t}) \in \{\boldsymbol{f_1}, \boldsymbol{f_2}, \ldots \boldsymbol{f_n}\}$. Defined earlier, a Critical Component refers to any constituent part, subsystem, or infrastructure facility crucial for upholding the critical services delivered by the CI sector. Then the functional states of the overall CI system $F_{CI}(t)$ can be expressed as:

$$\mathrm{F_{CI}}(\mathrm{t}) = min\{F_1(t), F_2(t) \ldots F_k(t)\}$$

Thus, $F_{CI}(t) \in \{f_1, f_2, \ldots f_n\}$.

This indicates that the sector's overall functionality is determined by its weakest component. The overall CI system's functionality state at time t is depended on the set of functionality states achieved by the individual critical components at time t. Also, it should be noted that there can be "n" number of possible functional states for each individual critical component. Thus, there is "n^k "of possible combinations for the overall CI system's functionality state.

Let $Q(t)$ be the set of possible combinations of functional states of critical components. Then $n\{Q(t)\} = n^k$. Also, it should be noted that the $F(t) \in Q(t)$.

Let $Q_{f_i}(t)$ $\left(Q_{f_i}(t) \subseteq Q(t)\right)$ be the set such that $\{F(t) = F_{f_i}(\mathrm{t})\} \in Q_{f_i}(\mathrm{t})$ *if* $\min\left\{F(t)\right\} = f_i$. Also, let's assume that there is $p \leq n^k$ number of elements in $Q(t)$ which satisfy the $\min\{F(t)\} = f_i$ (i.e. $n\left\{Q_{f_i}(t)\right\} = p$).

Thus,

$$F_{f_i}(\mathrm{t}) = \left\{F_{f_{i1}}(t), F_{f_{i2}}(t), F_{f_{i3}}(t), \ldots, F_{f_{ir}}(t) \ldots \ldots \ldots \ldots \ldots, F_{f_{ik}}(t)\right\}$$

where $F_{f_{ir}}(t) \in \{f_1, f_2, \ldots f_n\}$.

Then at time t the corresponding set of "functionality state" for the above set of "functional levels" can be written as follows,

$$S_{f_i}(\mathrm{t}) = \left\{S_{f_{i1}}(t), S_{f_{i2}}(t), S_{f_{i3}}(t), \ldots, S_{f_{ir}}(t) \ldots \ldots \ldots \ldots \ldots, S_{f_{ik}}(t)\right\}$$

where $S_{f_{ir}}(t) \in \{S_1, S_2, \ldots S_n\}$.

Let j be an index used to enumerate the possible functional state combinations in $Q_{f_i}(t)$ where each combination satisfies $min\{F(t)\} = f_i$. Specifically, j indexes the individual elements of the set, $Q_{f_i}(t)$ which consists of p possible combinations of the functional states $F_{f_i}(t)$. Then the probability of any functionality state of the overall CI sector ($F_{CI}(t) = f_i$) at time t can be calculated using Equation (2).

$$P(F_{CI}(t) = f_i) = \sum_{j=1}^{p} \left\{ \prod_{r=1}^{k} P\{S_{f_{ir}}(t)\} \right\} \tag{2}$$

Thus, this equation provides a comprehensive framework for assessing the probability distribution of functionality states in a CI sector, factoring in the interdependencies and states of its individual components.

- **Step 7: Compute the functionality of each CI sector as a summation of expected values of functionality states from $\mathbf{t = t_1}$ to $\mathbf{t = t_4}$:** In this stage, a functionality curve is constructed. As detailed in the preceding section 3, the functionality curve is formulated based on the expected values of functionality states. Subsequently, in step six, the probabilities of functionality states for each time slice are generated. Equation (1) is then applied to derive the system's functionality curve. It should be noted that the 'system' defined in Equation (1) can be a CI sector or a critical component. When deriving the functionality curve for the overall CI sector, $\boldsymbol{P}(\boldsymbol{F_{CI}}(\boldsymbol{t}) = \boldsymbol{f_i})$ in Equation (2) should be used as $\boldsymbol{P}(\boldsymbol{S_i})^{\boldsymbol{t}}$ in Equation (1). Bruneau et al., [81] introduced a mathematical definition for resilience loss (R) based on the functionality curve outlined in Equation (3), where $f(t)$ represents the functionality curve.

$$R = \int_{t_1}^{t_4} [100 - f(t)]dt \tag{3}$$

In the present study, resilience was defined as the integral of functional loss of the infrastructure from the time of disruption to the time of full recovery (t_1 = time of disruption, t_4 = time the infrastructure fully recovers), as proposed by Bruneau et al., [81]. Equation (3) is utilized to calculate the resilience loss for each critical component and for the CI sector. It should be noted that '100' represents the infrastructure quality at the time of disruption, which is denoted by F_1 in Fig. 2.

- **Step 8: Model validation and sensitivity analysis:** In this stage, model validation should be carried out. Model validation can be performed using available data or expert judgment. Afterward, sensitivity analysis can be conducted to pinpoint key and crucial factors within the CI system. Both the functionality states and resilience indicators are assessed as focal points for sensitivity analysis. For instance, all factors can be adjusted to high and low probabilities of operational states, after which the system's resilience is assessed over time.

4. Application of proposed methodology: case study

This section discusses the application of the proposed methodology for assessing resilience of CI system. The current study focuses

Table 2
Identified interdependencies between water, electricity, and transportation infrastructure sector.

Affected critical component	Indicator	Electricity	Water	Transportation
Pump station and distribution network	Building new facilities	Electricity is required for facility restoration and building the new facilities. Furthermore, electricity is required for the functionality of the pump house. The back up system will be affected by the functionality of the electricity sector.	Not affected	Roads are of utmost importance for the transportation of the materials and labour and accessing the asset/infrastructure facilities for restoration or repair activities of pump house.
	Asset backup Backup available duration Percentage of asset that have backup			Not affected
	Availability of interconnected service	Not affected		Roads are of utmost importance for the transportation of the materials and labour and accessing the asset/infrastructure facilities for restoration or repair activities of pump house.
Power plant	Availability of interconnected service Replacement of asset Building new facility Facility relocation	Not affected	Not affected	Roads are of utmost importance for the transportation of the materials and labour and accessing the asset/infrastructure facilities for restoration or repair activities of pump house.
	Time that CI is not able serve it function		Water distribution systems required for the functionality of the cooling system within the power plant.	Not affected
Transformers and transmission lines and grid stations	Facility relocation Building new facility Availability of interconnected service	Not affected	Not affected	Roads are of utmost importance for the transportation of the materials and labour and accessing the asset/infrastructure facilities for restoration or repair activities of pump house.
Road	Availability of interconnected service Functionality of communication system Time that CI is not able serve it function	Communication systems will be affected due to the disruption of the electricity. Furthermore, signaling system also become unfunctional due to unavailability of the electricity.	Not affected	Not affected
	Partially damage asset road	Not affected	Repairing activities of water pipe distribution network due to disruption may result partial damages to the road network.	Not affected

on the Sri Lankan electricity, transportation, and water infrastructure sectors as a case study. The details of the data collection process are provided in Appendix C.

4.1. Modelling of CI system using DBN

The following sections 4.1.1- 4.1.8 demonstrate the stepwise application of the proposed methodology.

4.1.1. Step one: Define the system boundaries and CI sectors that are considered for resilience assessment

As aforementioned, the current investigation has elected to focus on the development of a model based on the integration of electricity, water, and transportation infrastructure. The selection of these infrastructure components stems from their fundamental importance in sustaining urban functionality and their susceptibility to disruption during adverse events. Assets located in Colombo District, Sri Lanka were specifically included in the model. This deliberate choice is underpinned by the recognition of the increased vulnerability of this geographical location to inundation events, primarily attributable to flood occurrences. Within the context of disaster scenarios, the inundation resulting from floods has been identified as a principal disruptive force impacting CI systems and their components. Therefore, flood events were selected as the primary disruption mechanism to assess and mitigate vulnerabilities in urban infrastructure networks.

4.1.2. Step two: Identification of critical components in each CI sector within the system under assessment and identify the interdependency of the component with other sectors and all required information

During this phase, the collection of relevant data on critical components and asset types is preceded by expert judgment, as explained in section 3. Within the domain of electricity infrastructure, transmission lines, transformers, power plants, and grid stations emerged as critical asset types. Likewise, within the water infrastructure, critical attention was directed towards the water distribution system and pump stations recognizing as critical components. Similarly, based on expert judgment, road infrastructure was identified as the critical component within the context of transportation infrastructure. Moreover, the interdependencies among the selected CI systems were also identified during this step. Table 2 shows the identified interdependencies within the electricity, transportation, and water infrastructure sectors.

In the proposed methodology, the identified interdependencies between CIs are captured through directed arcs connecting nodes that represent infrastructure sectors (i.e., nodes for Water, Electricity, and Transportation) to nodes representing the critical components of other infrastructure sectors. Specifically, each infrastructure sector (e.g., water, electricity, and transportation) is modeled as a child node aggregating its critical components' overall functionality. These child nodes are connected to the indicators of critical components in other infrastructure sectors via directed arcs, signifying causal relationships and interdependencies. For example, the functionality of the electricity sector is linked to the indicators of critical components of the water sector, such as pump stations, through an arc. This connection reflects the dependency of the water infrastructure on electricity for operations, as depicted in Table 2. The arcs are defined based on expert judgment, operational dependencies, and evidence from literature, with their strengths quantified using Conditional Probability Tables (CPTs). DBN provides a dynamic and probabilistic framework for resilience assessment by incorporating these interdependencies.

4.1.3. Step three: Identification of critical component's functionality and constructing Markov chain depicting critical component's states considering it as sub systems of a main system

In this step, four functionality states (S_1, S_2, S_3, and S_4) of each critical component are defined. In addition to the primary resilience capacities, functionality states are influenced by several parameters. The resilience of the CI system is defined based on the resilience of its critical components as per Equation (2). The resilience of each critical component is determined using four different resilience capacities: anticipation, absorption, restorative, and adaptive. Each capacity was further decomposed into sub-indicators to evaluate these resilience capacities, as illustrated in Fig. 3. This system of indicators was established based on prior research conducted by the same scholars [55]. Then, BN structures were developed for each critical component within the electricity, water, and transportation infrastructures (See Fig. A.1, Fig. A.2, and Fig. A.3 in Appendix A). For this study, it is assumed that all resilience indicators exhibit only two states: "High" or "Low." In these BNs, three nodes were added to represent the functionality of the "Electricity," "Water," and "Transportation" infrastructures.

4.1.4. Step four: Estimate transition probabilities and convert each Markov chain to a set of DBNs

As shown in Table 1 and Fig. 4, the transition rates from state one (S_1) to state four (S_4) are defined by the respective transitional probabilities λ, μ, α, and δ. It is important to note that these transitional probabilities are ideally derived from historical data, if available. To determine the values for states one through four, the CPTs for the corresponding nodes are subsequently used, guiding the state of functionality for each node.

Fig. 6 depicts the derived DBN resulting from the translation of the Markov chain, showing all potential contributing factors. Notably, the resilience indicator nodes within the same time slice are represented by the contributing causes for the resilience capacity, which are connected by normal arcs. Furthermore, interdependencies are illustrated by the normal arcs linking the sector nodes, which impact the resilience indicators identified in step 02. The CPTs need to be established for all child nodes. Table 3 shows the CPTs for the nodes representing 'Electricity,' 'Water,' and 'Transportation'. The functionality states of these three nodes have four states (S_1, S_2, S_3, and S_4). However, when defining the CPTs for the interdependencies, it is more complex to establish them with four states in the nodes representing overall CI systems. Therefore, to build a preliminary model, the functionality states of the nodes representing the overall

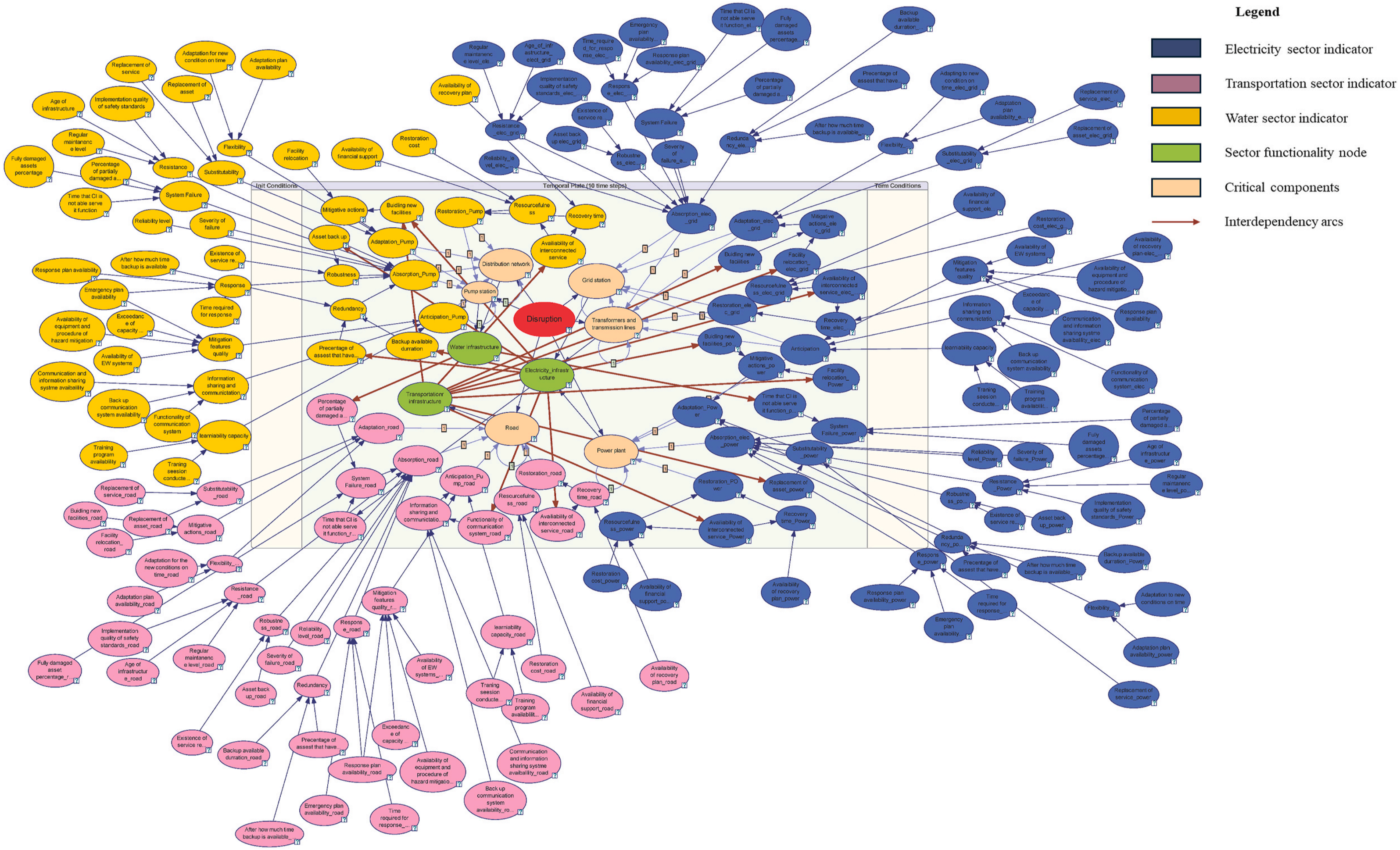


Fig. 6. DBN structure for water, electricity, transportation infrastructure system with interdependencies.

CI system are assumed to have two extreme states (i.e., Yes/No). Accordingly, if the critical components are in either state S_1 or S_4, the overall CI system node functionality is set to 'Yes.' Otherwise, it is set to 'No.' Based on this, CPTs for the CI system nodes were defined as illustrated in Table 3.

For the remaining child nodes, the corresponding conditional probabilities capturing the interdependencies are established through expert judgment, as demonstrated in Table 4. In this case study, the Analytic Hierarchy Process (AHP) is used to assess the effects of parent nodes on child nodes, which are represented by conditional probabilities. AHP was utilized to determine the weights of contributing factors through expert judgments. It is important to note that these weights differ across systems due to variability in their operational conditions and external environments. As a result, the weighs heavily rely on expert system evaluations. The importance weights of the causative elements are presented in Table D1 in Appendix D. Additionally, the impacts of the parent nodes' contributing parameters are regarded as independent. Therefore, all parent nodes' influence on the associated child nodes is modeled using Leaky "Noisy-OR" models.

4.1.5. *Step five: Compute the probability of each functional state of each critical component*

This step calculates the probability of each functional state of the critical components using the developed DBN. The DBN and computations were performed in the GeNIe BN modeler [82]. The DBN over 30-time slices is depicted in Fig. 6. While the time slice is considered to represent an hour in this analysis, it can also represent a second, minute, day, week, or year. For the resilience assessment, status of the node "Disruption" is set to 'High' during t = 1 to t = 30.

4.1.6. *Step six: Compute the probability of each functional state of the CI sector*

In this step, the probability distribution for each functionality state of each sector is determined as outlined in Section 3.

4.1.7. *Step seven: Compute the functionality of each CI sector as a summation of expected values of functionality states $t = t_1$ to $t = t_4$*

As previously described, the functionality curve is used employed to assess the resilience of the system. The expected levels of functionality (i.e., F_1, F_2, F_3, and F_4 in Fig. 2) are defined to calculate the expected values of the functionality states. These expected functionality levels are based on expert judgment for each critical component. Table 5 presents the expected functionality levels utilized in this study. Subsequently, Equation (2) is applied to derive the system's functionality curve.

Fig. 7 (a) and (b) depict the functionality curves of CI sectors and their individual components over a 30-hours period following a disruptive event. Fig. 7 (a) focuses on the functionality of three CI sectors: water, electricity, and transportation, while Fig. 7 (b) provides a more detailed breakdown of the functionality curves for the critical components within these sectors. Both figures demonstrate the dynamic recovery process and the interdependencies among these systems, offering valuable insights into their vulnerabilities and the restoration sequence.

In Fig. 7 (a), transportation infrastructure exhibits the fastest recovery, achieving 90 % functionality by the 8^{th} hour and fully recovering by the 12^{th} hour. This rapid restoration highlights the importance of transportation in facilitating the mobility of repair crews, equipment, and resources necessary to recover other sectors. On the other hand, electricity infrastructure experiences a sharp

Table 3
CPT for nodes (a) Electricity, (b) Water and (c) Transportation.

Power plant	S1																S2															
Grid Station	S1				S2				S3				S4				S1				S2				S3				S4			
Transformers	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4
Yes	1	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
No	0	1	1	0	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Power plant	S3																S4															
Grid Station	S1				S2				S3				S4				S1				S2				S3				S4			
Transformers	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4
Yes	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	1	0	0	1
No	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1	0	1	1	0

(a)

Pump station	S1				S2				S3				S4			
Distribution Network	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4
Yes	1	0	0	1	0	0	0	0	0	0	0	0	1	0	0	1
No	0	1	1	0	1	1	1	1	1	1	1	1	0	1	1	0

(b)

Road infrastructure	S1	S2	S3	S4
Yes	1	0	0	1
No	0	1	1	0

(c)

Table 4
Conditional probability table for the interdependencies.

Affected critical component	Indicator	Electricity		Water		Transportation	
		Yes	No	Yes	No	Yes	No
Pump station and distribution network	Building new facilities	0.59	0.48			0.74	0.3
	Asset backup	0.69	0.09				
	Backup available duration	0.47	0.12				
	Percentage of asset that have backup	0.72	0.1				
	Availability of interconnected service					0.63	0.21
Power plant	Availability of interconnected service					0.36	0.12
	Replacement of asset					0.32	0.09
	Building new facility					0.12	0.05
	Facility relocation					0.13	0.25
	Time that CI is not able serve it function			0.82	0.05		
Grid	Facility relocation					0.45	0.21
	Building new facility					0.39	0.05
	Availability of interconnected service					0.57	0.12
Road	Availability of interconnected service	0.74	0.12				
	Functionality of communication system	0.13	0.06				
	Time that CI is not able serve it function	0.71	0.14				
	Partially damage asset road			0.45	0.83		

Table 5
The expected level of functionality (F_i) for functionality states of the systems.

Functionality state	Water	Electricity	Transportation
S_1	100 %	100 %	100 %
S_2	10 %	20 %	15 %
S_3	35 %	35 %	40 %
S_4	98 %	99 %	98 %

drop in functionality, reaching its lowest point at the 4th hour. Recovery efforts accelerate between the 6th and 12th hours, with full restoration occurring by the 20th hour. Water infrastructure demonstrates the slowest recovery, with functionality dropping to approximately 20 % at the 5th hour. It's recovery is heavily influenced by the restoration of electricity and transportation, achieving full functionality only after 24 hours. These trends emphasize disruptions' cascading impacts and interdependencies' critical role in recovery.

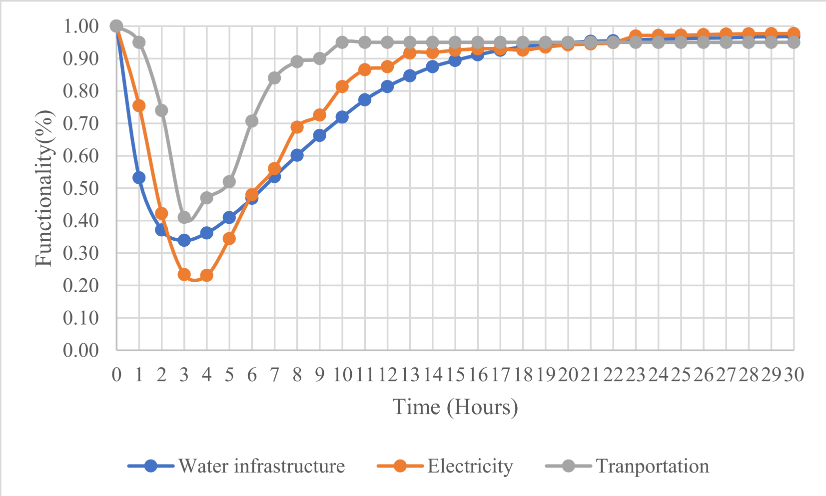
Fig. 7 (b) provides a more granular perspective, illustrating the recovery patterns of individual components within the main infrastructure sectors. Road infrastructure is the quickest to recover, achieving 90 % functionality by 6th hour and full recovery by 8th hour. This rapid recovery is crucial as it enables access to repair sites and the transportation of necessary resources. Grid stations and transmission lines, which are essential for electricity distribution, recover more slowly due to the complexity of repairs and their dependency on road access and operational power plants. Grid stations achieve 80 % functionality by 12th hour and full recovery by 20th hour. Components of the water infrastructure, such as pump stations and distribution networks, recover even more gradually. Their restoration is influenced by the delayed recovery of electricity infrastructure, with full functionality achieved only after the 24th hour. The recovery curves highlight the significant interdependencies among infrastructure sectors and components. For instance, the restoration of water infrastructure depends on the recovery of electricity for operating pump stations and distribution networks, as well as on transportation for delivering repair crews and materials. Similarly, delays in restoring grid stations and transmission lines can impede the recovery of power plants and, in turn, affect the functionality of dependent systems.

These figures underscore the importance of prioritizing recovery efforts based on interdependencies and vulnerabilities. Transportation infrastructure, as a critical enabler, must be restored rapidly to facilitate repairs in other systems. The timely restoration of electricity infrastructure, particularly grid stations and transmission lines, is essential for resuming the operation of water distribution systems and other essential services. The insights provided by Fig. 7 can help policymakers and disaster recovery teams allocate resources effectively, minimize system downtime, and enhance infrastructure resilience during future disruptions.

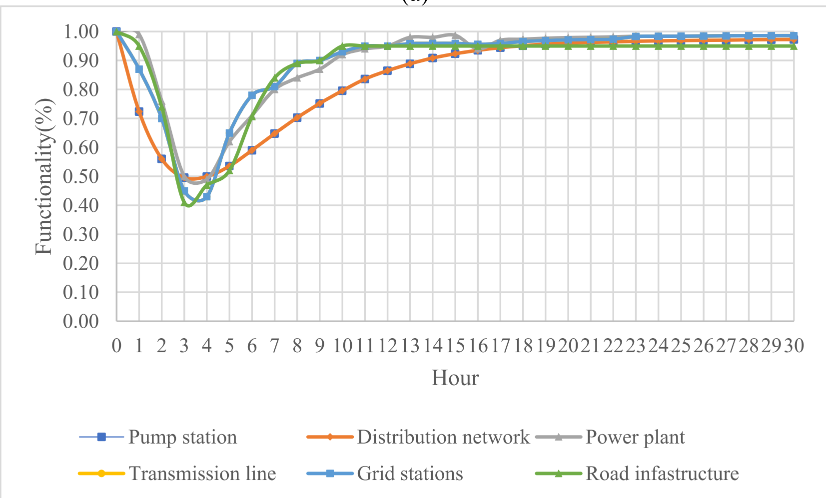
4.1.8. Step eight: Model validation and sensitivity analysis

As the final step, validation was performe. The validation and verification of the resilience assessment for the case study require data on functionality and system properties. However, obtaining the necessary historical data for each indicator is often challenging. The model was validated using expert judgment. This approach, while common in data-scarce contexts, was implemented with careful consideration to minimize potential confirmation bias [83–86]. In this study, the model was validated by comparing the changes in resilience levels predicted by model with expert judgments against changes in the root node indicators.

During data collection, experts were asked to evaluate the change in resilience levels on a (−2)-(+2) Likert scale (−2: Very High reduction, −1: Slight reduction, 0: No Change, +1: Slight positive increment, +2: Very High positive increment) relative to the current level of resilience against given changes in root node indicators. For example, experts assessed the change in the resilience level in the absence of a 'Backup system,' compared to the presence of the current 'Backup system'. It is important to note that the baseline



(a)



(b)

Fig. 7. Derived functionality curves for (a) Sector wise (b) Critical component wise.

resilience is determined by the current capacity of each respective indicator (e.g., 'Backup system').

Resilience loss for each change in the indicators was calculated based on the functionality curve predicted by the model, and corresponding changes in resilience were assessed. At the same time, data was collected from the experts on the relative change in resilience based on their judgment. These steps were executed for each individual component. Subsequently, a Chi-Square test (See Table A 3 in Appendix A) was conducted to compare the variations in resilience levels predicted by the model with the expert judgments for each critical component. Table 6 presents a summary of the Chi-Square test results from the validation exercise. Notably, the P-values for all infrastructure sectors are less than 0.05, indicating a significant relationship between the variations in resilience predicted by the model and the expert judgments. An Odds Ratio (OR) test was also performed to check the direction of the association. The OR test results are depicted in Table 6. It should be noted that the OR for all infrastructure categories is greater than 1, indicating a positive relationship between the variation of model-predicted values and expert judgment. These findings suggest that the model output aligns with the expectations of the experts.

Table 6
Results of the Chi-square test for the variation of model-predicted values and expert judgment.

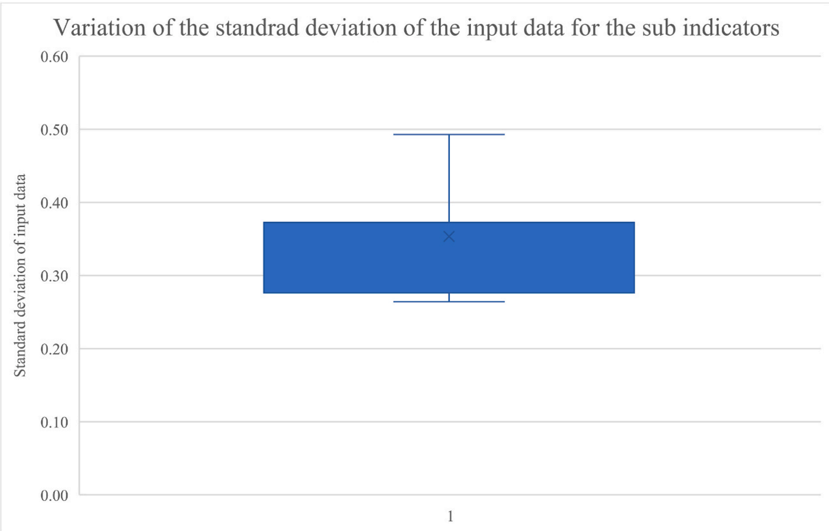
Chi-Square test statistics	Pump station and distribution network	Road infrastructure	Transformers and grid station	Power plant
Chi-Square value	25.04	40.92	20.20	38.68
Critical value	9.488	9.488	9.488	9.488
P-value	4.93999E-05	2.79727E-08	0.000457	8.1E-08

5. Discussion

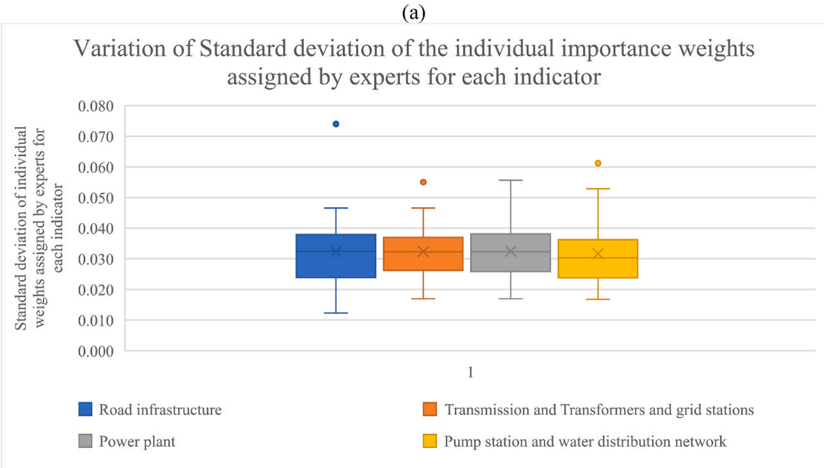
5.1. Assumptions and limitations

Several issues should be addressed in the proposed approach. The methodology requires establishing the probabilities for the parent nodes and the conditional probabilities for the interdependencies and the influence of parent nodes on their child nodes. Expert judgment is utilized in this study, which constitutes a limitation due to the difficulty in obtaining data to establish these probabilities. Fig. 8 shows the variation of standard deviations for different data types collected in the study. Fig. 8 (a) shows that the standard deviation of input data for the sub-indicators ranges from 0.28 to 0.37, indicating a certain level of agreement among the input data. Additionally, Fig. 8 (b) shows the box and whisker plots for the standard deviation of the importance weights for the indicators assigned by individual experts for each critical component. It can be noted that there is a higher deviation in the individually assigned weights for some sectors in Fig. 8 (b), particularly in the road, transmission, and transformers, grid stations, pump stations, and water distribution networks. However, there is general agreement among the experts on the importance weights assigned to the sub-indicators (parent nodes) influencing the main indicators (child nodes). Another dataset collected during the present study is the interdependencies. Fig. 8 (c) presents variations in standard deviation of input data assigned by the experts, reflecting interdependencies among the CIs. The standard deviations of input data for the interdependencies vary from 0.32 to 0.49, indicating slight agreement among the experts about interdependencies among CIs.

Since the data for the study is mainly from subjective sources, the variation in input data significantly affects the model results. The standard deviation of input data gathered from experts indicates a consensus to a certain degree. Therefore, the proposed methodology is moderately reliable for predicting resilience. However, the robustness of the proposed methodology can be enhanced by engaging

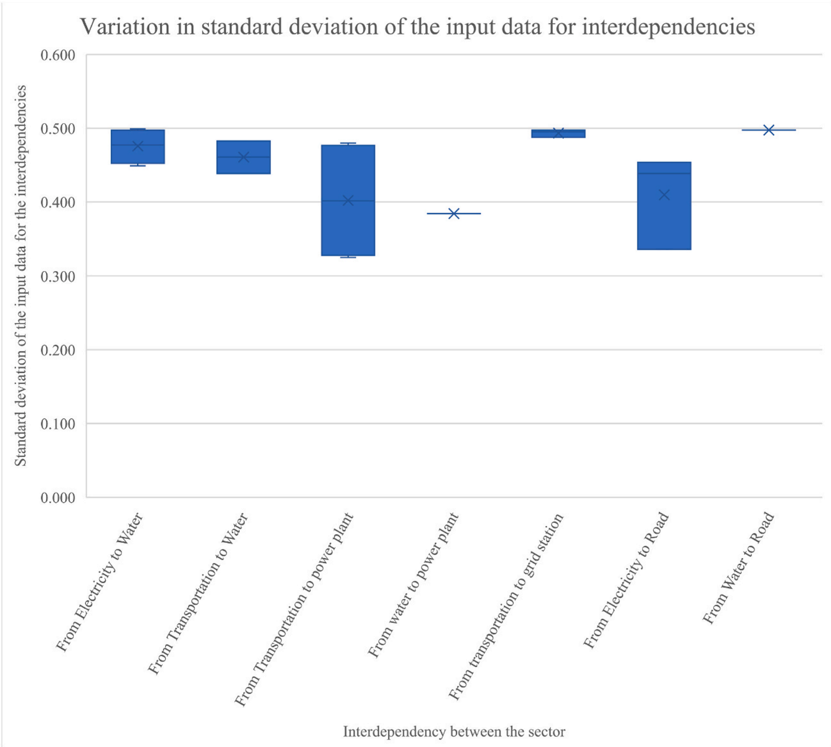


(a)



(b)

Fig. 8. Variations in standard deviation of input data



(c)

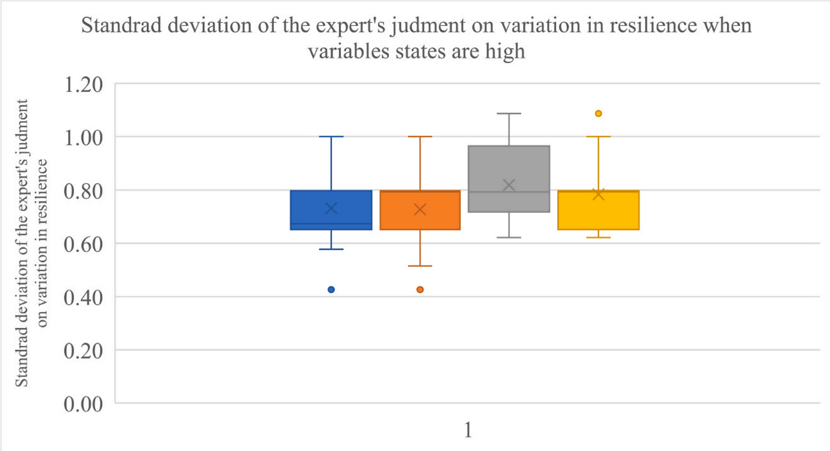
Fig. 8. (*continued*).

more experts and incorporating empirical data. Furthermore, Fig. 9 (a) and (b) show variation in standard deviations of the expert's judgments on the variation of resilience level for higher and lower states of the variables respectively. The analysis of expert judgments on resilience variation for four infrastructure types under high and low variable states reveals moderate consensus overall, with some variability across infrastructure types. The pump station and distribution network show moderate variability under high states, indicating moderate agreement among experts, whereas roads exhibit narrower IQRs, suggesting stronger consensus. Transmission lines and grid stations show moderate variability with occasional outliers, while power plants consistently demonstrate the least variability and strongest consensus across both conditions. The findings highlight areas with strong expert agreement. While expert-based validation is a well-established approach in resilience modeling, we acknowledge its limitations, particularly the risk of confirmation bias. To mitigate this, a diverse panel of experts from multiple sectors was engaged in this study to reduce individual biases and enhance the robustness of the validation. Furthermore, future work aims to incorporate empirical or independent data sources when available to strengthen the validation process further. Additionally, to improve the proposed method, more advanced functionality models should be applied. In the model, when a disruption occurs, the initial probability of state $S_1 = 1$ indicates that system's functionality is at its peak at the moment of disruption. In this study, functionality degradation is presumed to be minimal, and the loss of functionality due to this degradation is considered negligible compared to the loss caused by disruptions. Therefore, the functionality before the disruption is assumed to be at its maximum value of 1 (i.e., $S_1 = 1$).

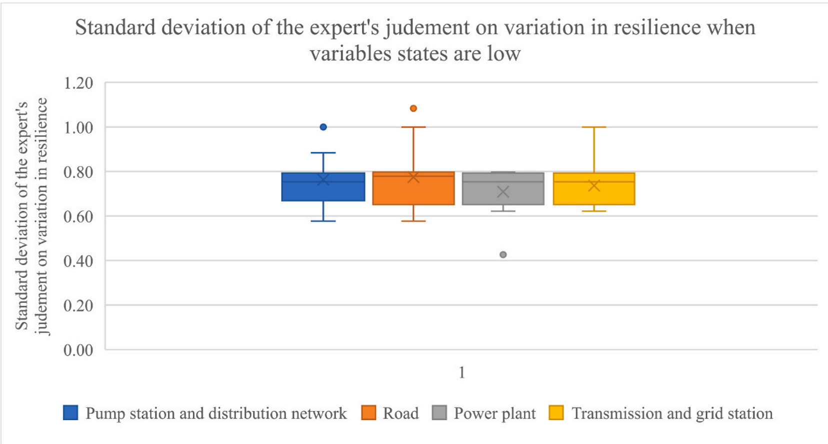
The DBN-based framework for measuring resilience can be adapted and applied to any complex industrial infrastructure in real-world scenarios. Conditional probabilities will vary across different systems due to differences in resilience capacities, such as anticipation, absorption, adaptation, and restoration. In this study, equal weighting is assumed for the resilience capacities of all critical components considered. However, to accurately assess the resilience of various systems, different arrangements and conditional probabilities (node weights) must be used to reflect the unique system configurations and the organization's specific concerns. Furthermore, the case study did not consider the dynamic characteristics of the indicators in the root nodes. In the real world, the capacities of the relevant organizations change dynamically. This aspect was not considered in the case study conducted in the present study.

5.2. Modelling resilience under multi-hazard situation

The case study presented in the above sections demonstrates the validity of the proposed methodology for resilience assessment of CI under single-hazard scenarios. However, in reality, CI systems frequently encounter multiple hazards throughout their lifecycle, a factor often overlooked in the existing literature. The proposed methodology in this study could be extended to address this issue. This extension is not merely a theoretical proposition but a practical enhancement that can significantly improve the utility of the model in real-world applications. The multi-hazard approach acknowledges the complex interactions between different types of hazards and



(a)



(b)

Fig. 9. Variation of the standard deviation of the expert's judgement on variation in resilience for different states of the variables.

their cumulative impact on CI, thereby offering a more comprehensive and realistic resilience assessment.

In a multi-hazard context, the proposed methodology must incorporate additional variables and dependencies to capture the interactions and correlations between different hazards. To extend the proposed methodology to multi-hazard scenarios, identifying hazards and their interactions is critical during the first and second steps. These hazards may include natural hazards (e.g., earthquakes, floods), technological hazards (e.g., cyber-attacks, power outages), and socio-political hazards (e.g., terrorism, civil unrest). Understanding the interactions between these hazards is crucial for accurately representing real-world scenarios.

Multi-hazard scenarios should also be developed to encapsulate the joint occurrence of multiple hazards. These scenarios should be based on historical data, expert judgment, and probabilistic assessments, with each scenario defining the sequence and interdependencies of hazard events. During the fourth step, the BN structure should be extended to include nodes representing different hazards and their interactions. The CPTs for these nodes must reflect the likelihood of each hazard given the occurrence of others. This requires integrating data from diverse sources and ensuring that the CPTs accurately represent real-world dependencies.

Furthermore, in a multi-hazard context, state of the CI and its components may transit differently based on combination of hazards. The model must account for these transitions by updating the state transition probabilities to reflect multi-hazard impacts. To illustrate the application of the extended model, a case study on the water infrastructure sector is provided. For demonstration purposes, data collection for the modelling task was conducted with hypothetical experts, as this aspect falls outside the scope of the current study. The following scenarios were considered to present the extension of the proposed methodology.

5.2.1. Scenario 01: Second disruption occurs after the system is fully recovered

In this scenario, two disruptions occur at different times. For demonstration purposes, the first hypothetical flood event occurs at time t = 0 (Disruption 01). Subsequently, at t = 30, when the water infrastructure's critical components have fully recovered, a hypothetical landslide (Disruption 02) occurs in the same area due to high-intensity rainfall. The respective BN structure for this scenario can be modeled using the previously utilized software, as depicted in Fig. 10. After obtaining the probabilities of functionality states for the critical components, the functionality curve can be developed as explained in Sections 3. The functionality curve for this scenario is depicted in Fig. 11.

5.2.2. Scenario 02: Second disruption occurs before the system is fully recovered

Another possible scenario in a multi-hazard context is when the second disruption occurs before the system has fully recovered. As illustrated in Fig. 11, the system fully recovers at $t = 23$ under a single-hazard scenario. In this alternate scenario, a subsequent hypothetical landslide (Disruption 02) occurs at $t = 15$. The corresponding BN structure for this scenario can be modeled by setting the temporal order of the arc between the disruption node and the critical component in the BN structure, as shown in Fig. 10. This adjustment indicates that the second disruption occurs at $t = 15$. Fig. 12 shows the functionality curve derived under this scenario.

The extension of the DBN model for resilience assessment from a single hazard to multi-hazard context represents a significant advancement in the field of CI protection. By incorporating multiple hazards and their interactions, the model offers a more comprehensive and realistic assessment of resilience, which is essential for effective risk management and mitigation. While challenges remain, ongoing advancements in data collection, modelling techniques, and computational resources offer potential solutions. Future development and application of multi-hazard resilience assessment models will undoubtedly play a critical role in safeguarding CIs against an increasingly complex and interconnected risk environment.

5.3. Novelty and contribution of the proposed methodology

The present study introduces a novel approach to resilience assessment CI systems by addressing gaps in existing methodologies through a robust, dynamic, and probabilistic framework. Leveraging DBNs, the study dynamically captures the temporal evolution of system functionality, enabling detailed assessment of transitions over time, which overcomes the limitations of static and steady-state models seen in prior works (see Table 7). Unlike deterministic or scenario-based approaches, the framework incorporates detailed probabilistic modeling to quantify uncertainties in functionality states and transitions, enhancing the robustness of resilience evaluations. The study broadens the scope of interdependencies by comprehensively modeling physical, operational, and functional connections, addressing cascading failures and systemic impacts holistically. It also enables resilience modeling at both the component and sector levels, providing granular, multi-scale insights that traditional system-level analyses often neglect. Furthermore, the methodology dynamically evaluates system state transitions, quantifying resilience as the summation of expected functionality states over time, capturing detailed system behaviors more effectively than predefined restoration curves. By integrating these elements, the proposed approach bridges critical gaps in existing research, offering a comprehensive framework for modeling interdependent CI systems, considering multiple functionality states, and dynamically evaluating temporal and probabilistic aspects. This study provides

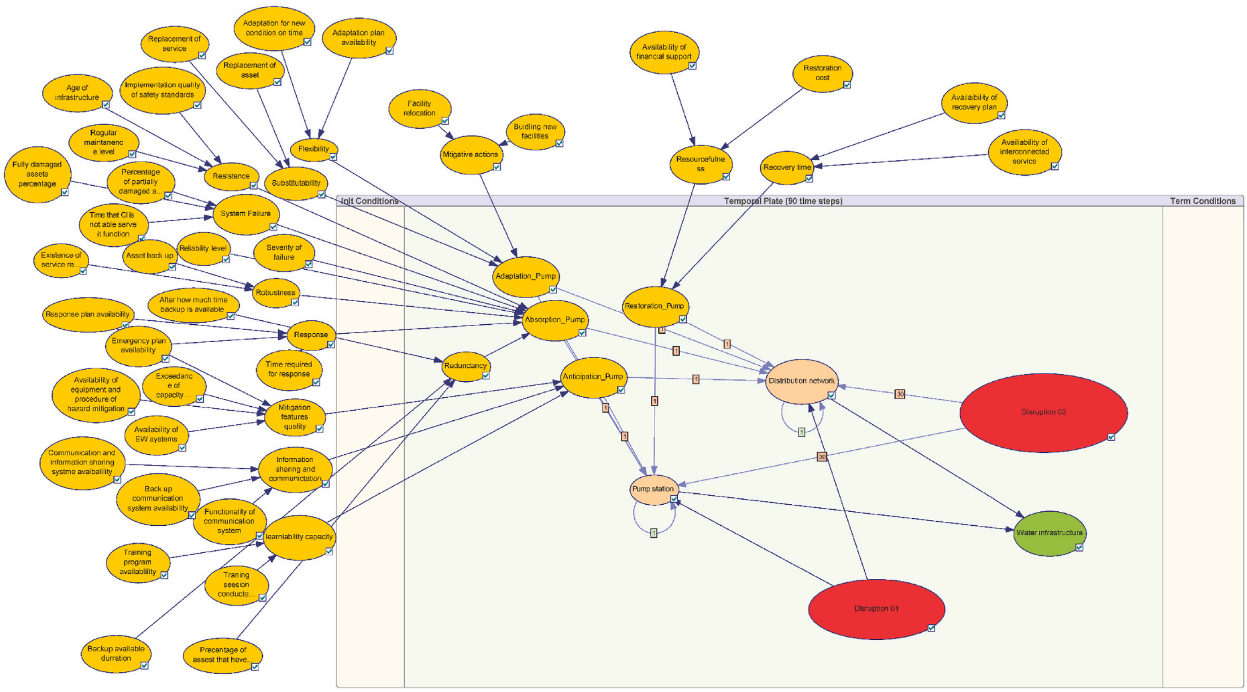


Fig. 10. BN structure for multi hazard type _Scenario 01.

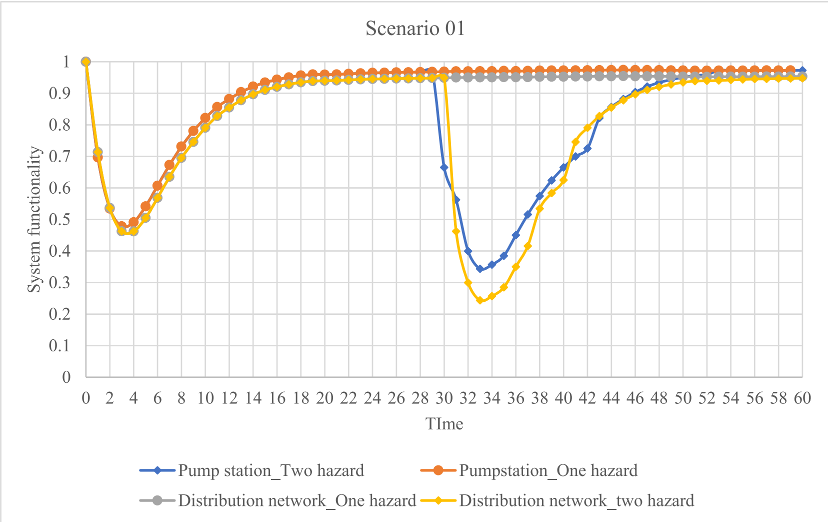


Fig. 11. Functionality curve for scenario 01.

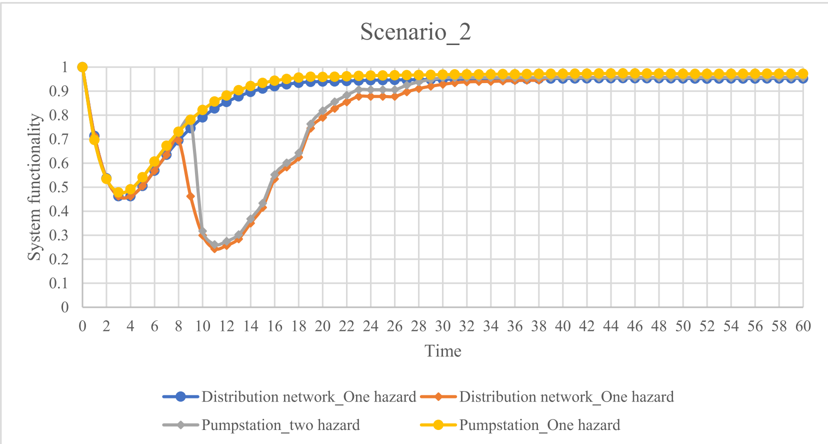


Fig. 12. Functionality curve for Scenario_2.

a significant advancement in resilience assessment, delivering a robust and adaptable tool to enhance the sustainability and reliability of CIs.

6. Conclusion

Previous studies have suggested various methods for assessing CI system resilience, but these often overlook the interdependencies that are intrinsic to CIs. These conventional methods are appropriate when the resilience measurement relies exclusively on the intrinsic characteristics of the system. However, including human and external factors in modeling introduces uncertainty and dynamism to resilience. Therefore, resilience evaluation necessitates a probabilistic and dynamic approach, augmented by subjective judgments, to achieve a more precise and comprehensive assessment. Therefore, a novel methodology based on DBN has been proposed to assess the resilience of CI systems by incorporating the dynamic characteristics of system functionality and interdependencies.

This method develops a model representing the CI system and derives the functionality curve through functionality states. By defining system functionality in terms of these states, the methodology can assess system functionality in a probabilistic and dynamic manner and generate the system's functionality profile. Moreover, it (i) integrates both subjective and objective data, (ii) updates the model with the arrival of new evidence, and (iii) evaluates the system's functionality over time.

Furthermore, a case study was conducted in the context of the Sri Lankan electricity, water, and transportation sectors. By applying the methodology to a real-world case, it has been confirmed that the proposed methodology can produce a dynamic functionality profile. This dynamic functionality profile allows decisionmakers to better understand the resilience capabilities of individual components, monitor component functionality, assess safety measures, prevent unwanted disruptions, and identify viable operational system improvements. The case study demonstrates that the model developed using proposed methodology can produce accurate and

Table 7
Comparison of the proposed approach with existing studies on CI resilience assessment.

Reference	Modelling method	Temporal Modeling of Resilience	Probabilistic assessment	Scope of Interdependencies	Granularity of Analysis	Dynamic Characteristics of the System
Proposed approach	DBN	Captures temporal evolution dynamically using a DBN, enabling continuous assessment of system functionality state	Incorporates detailed probabilistic assessment through DBN, modeling uncertainty and dynamic transitions in functionality states	Models physical, operational, and functional interdependencies comprehensively, addressing cascading and systemic impacts holistically	Provides granular analysis at both the component and sector levels, enabling in-depth understanding of individual components' behavior	Dynamically evaluates transitions in system states over time, quantifying resilience as a function of expected functionality levels
[60]	DBN	Uses DBNs to predict steady-state availability and time for resilience evaluation	Focuses on steady-state availability and time under fixed assumptions about shocks and repairs	Primarily models series, parallel, and voting system dependencies but lacks a broader consideration of interdependencies	Analyzes resilience at a generalized system level, focusing on abstract system representations	Captures availability changes due to degradation and repair but does not fully explore functionality transitions
[61]	DBN	Time-varying resilience for flood-affected housing infrastructure	Focuses on field-survey-based resilience parameters with conditional probabilities derived from expert opinion	–	Models resilience at a system level for specific infrastructure	–
[57]	Network-based approach	Uses time-dependent resilience metrics based on performance curves, considering discrete stages (resistance, absorption, restoration)	Limited probabilistic modeling; primarily deterministic or scenario-based analysis for cascading failures and restorations	Focuses on unidirectional interdependencies (e.g., power-to-gas), with limited consideration of broader interconnections	Operates at the system level; lacks detailed modeling at the component level	Models restoration processes and average performance curves under fixed scenarios; less emphasis on dynamic system state transitions
[62]	DBN	Time-dependent resilience assessment but focuses on limited time steps	Provides a probabilistic framework incorporating uncertainties in system states and inputs through Bayesian models	Models interdependencies between system components with a focus on physical and structural relationships	Evaluates resilience at a generalized system level with illustrative examples of transportation and national systems	Captures system recovery and restoration processes but focuses on predefined variables and scenarios
[63]	Agent based modelling	Utilizes a time-phased approach, focusing on steady-state metrics and transition phases between disruptions and recovery	Integrates probabilistic measures for resilience capabilities like robustness, rapidity, and recovery but focuses on predefined metrics	Explores interdependencies in multi-layer systems using a hybrid modeling approach but focuses primarily on physical dependencies	Focuses on system-level resilience through multi-layer modeling but lacks component-level insights	Analyzes transitions between resilience phases (disruptive, recovery, steady-state) but with predefined metrics for changes
[59]	Dynamic Network flow	Utilizes a rolling planning horizon and dynamic network flow models to simulate temporal recovery and asset operability	Incorporates stochastic asset failure using scenario tree generation but does not model uncertainty in flow redistribution	Considering multiple dependency relations (stochastic failure propagation, resource input, logic) among interdependent systems	Focuses on system-level and asset-level modeling with a detailed representation of network flows and repair resources	Captures changes in asset operability and network flows during disruption and recovery phases

reliable results.

However, two challenges that arose during the investigation call for further exploration. First, while the present investigation focused on discrete time-dependent processes, the operational processes are continuous. This indicates that the discrete states of the BN's child nodes are present, which could be addressed using a continuous DBN. The simplicity of modeling CI system robustness while accounting for interdependencies with a DBN was prioritized in this study, but it did not consider the use of a continuous model. Additionally, past data could be used to determine the transition stages and probabilities of the child nodes. A data-driven approach could help address the model's epistemic uncertainty and establish the conditional probability tables.

Moreover, the proposed methodology could be expanded to include resilience assessment of CIs under multiple hazards. The authors have demonstrated how the methodology could be extended to assess resilience under multiple hazards, and this extension is recommended for future research. The extension of the proposed methodology to multi-hazard contexts introduce following challenges:

- **Data availability and quality**: Comprehensive data on the joint occurrence and impact of multiple hazards is often limited. Improving data collection and sharing practices is essential for enhancing the model's accuracy.
- **Complexity of interactions**: The interactions between hazards can be highly complex and non-linear. Capturing these interactions accurately requires sophisticated modeling techniques and substantial computational resources.
- **Uncertainty management**: The inherent uncertainties in predicting hazard occurrences and their impacts are magnified in a multi-hazard context. Advanced uncertainty management techniques are essential for ensuring the model's predictions remain reliable.
- **Integration with other models**: Integrating the Dynamic Bayesian model with other types of models (e.g., physical models of infrastructure systems, economic impact models) can provide a more comprehensive assessment. Developing seamless integration methods is a key area for future research.
- **Real-Time data integration**: Implementing real-time data integration and ensuring that the model can process, and update in response to this data in a timely manner is crucial. This requires advances in data processing technologies and algorithms.

Additionally, the model developed through this proposed methodology offers several benefits. First, it improves the accuracy of resilience assessments by considering hazards and their interactions, leading to better-informed decision-making and more effective mitigation strategies. It also ensures comprehensive risk management by promoting a holistic view of risk, where interdependencies between CIs are explicitly accounted for, resulting in more robust preparedness plans. Furthermore, understanding the combined impacts of multiple hazards enables CI operators and emergency responders to develop more effective preparedness and response strategies, such as implementing mitigation measures for floods following earthquakes. The model also optimizes resource allocation by predicting the cumulative impacts of disasters on CIs, which is crucial during emergencies with limited resources. Lastly, the insights gained from resilience assessments can inform policy and long-term planning, allowing policymakers to design regulations and standards that enhance the resilience of CIs to a broader range of disasters.

CRediT authorship contribution statement

Bawantha Rathnayaka: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Dilan Robert:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Varuna Adikariwattage:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Formal analysis, Conceptualization. **Chandana Siriwardana:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Conceptualization. **Erica Kuligowski:** Writing – review & editing, Validation, Supervision. **Sujeeva Setunge:** Writing – review & editing, Supervision, Project administration. **Dilanthi Amaratunga:** Writing – review & editing, Supervision.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to proofread. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Additional figures and tables

Table A 1Overview of different modeling techniques used in resilience assessment of CIs (Adopted from: [42,43,45]).

Modelling techniques	Input data	Advantage	Disadvantage	Interdependency representation	Complexity	Maturity
Descriptive table	Expert Judgment	• Intuitive representation • Easy implementation	• Requiring sufficient experience • Depending on the hazard scenario • Potentially biased	Descriptive terms, system level	Very low	High
Survey based Matrix	Survey data	• Simple representation	• Potentially biased • Requiring calibration	Coefficient, system level	Low	Medium to high
Correlation Analysis	Historical data	• Interpreting interdependencies with coupling strength and time lag	• Requiring functionality recovery data • Assuming stationary in time series analyses	Pearson correlations, cross correlation coefficients, system level	Low	Medium to high
Network Model	Topology capacity, flow	• Intuitive representation • Capturing interdependencies at component and system levels	• Requiring the complete knowledge of network features • Computationally expensive for large networks	Adjacency matrix, weight matrix, component level and system level	Medium to high	High
Input-Output Model	Inter sector transaction data	• Evaluating economic cascading impacts • Simple linear modelling	• Not applicable to forecasting • No representation of redundancy • Only economic impact	Interdependency coefficient matrix, system level	Medium	Medium to high
Computable generalized equilibrium	Inter sector transaction, elasticity	• Capturing static and dynamic nonlinear socioeconomic interdependencies	• Limited to economic impact only • Requiring a large amount of data	Interdependency coefficient matrix, system level	High	Medium to high
Discrete event simulation	Expert judgement, simulation data	• Explicit cause consequence analysis	• Requiring expert knowledge and assumptions for setting up causal relations	Possible scenarios and associated probabilities; component-level and system-level	High	Medium to high
Agent Based model	Expert experience and judgment	• Dynamic model • Considering decisions and consequences	• Difficult to calibrate agent behaviour • Modelling reactions after a perturbation rather than a whole picture	Predefined rules; component-level	Medium to high	Medium
System dynamics	Expert knowledge	• Dynamically simulating causes and effects in an evolving process with feedback	• Requiring expert knowledge and assumptions to establish relations and diagrams	System dynamics diagrams; component-level	Medium to high	Medium
Bayesian network	Simulation data, field measurement, expert judgement	• Generalized framework for handling data with large uncertainties	• Requiring variable discretization • Computationally expensive for large problems	Directed graphs; component-level	Medium to high	Medium
Optimization	Mathematical formulation form operational research	• Generalized framework for simulating and mitigation and restoration decisions	• Computationally expensive for large problems	Constraints of resource, precedence, budget, and time; component-level and system-level	High	Medium to high
Population mobility model	Empirical data, simulation data	• Capturing human mobility and location choices	• Assuming certain mobility decisions • Requiring a large amount of travel data	Logit model; gravity model, random walk algorithm; system-level	Medium	Medium
Aggregate supply and demand model	Profit data, spending data, price	• Comprehensive assessment of commodity flow	• Limited to system level interdependencies only	Mult attribute utility model; system-level	Medium	Medium
Machine learning	Social media data, new, simulation data	• Processing big data effectively and efficiently	• No physical insights • Potentially biased	Artificial intelligence; system-level	Low to high	Low

******Description of the complexity levels********

- **Very Low:** Requires minimal computational effort and is straightforward to apply, typically relying on simple methods like expert judgment or descriptive analysis
- **Low:** Involves modest computational effort and data requirements. Methods are relatively simple to implement but may need basic calibration
- **Medium:** Requires moderate computational resources, structured data inputs, and more advanced modeling techniques
- **High:** Demands significant computational effort, large data sets, and advanced methodologies, often involving complex simulations or optimization models

******Description of the Maturity levels ********

(continued on next page)

(*continued*)

Modelling techniques	Input data	Advantage	Disadvantage	Interdependency representation	Complexity	Maturity

- **Low:** The methodology is in its early stages of development or application. It may lack extensive validation and practical implementation in real-world scenarios.
- **Medium:** The methodology has been applied in some contexts and demonstrates moderate validation. However, its application may still be limited to specific use cases or controlled environments.
- **High:** The methodology is well-established and widely accepted in the field. It has been extensively validated, applied in diverse real-world scenarios, and has proven reliability.

Table A 2Overview of resilience assessment of the interdependent CIs studies.

Reference	Objectives	Time-dependent Analysis	Modelling method	Selected infrastructure	Interdependency Consideration
[60]	Develop a CI resilience metric based on reliability engineering	Yes	DBN	–	–
[61]	Develop a DBN framework to quantify housing resilience against floods	Yes	DBN	House	No
[57]	Extend resilience frameworks to model and evaluate interconnected systems during joint restoration	Yes	Network- based approach	Electricity, Gas	Yes
[62]	Assess time-dependent resilience of engineering systems using resilience indicators	Yes	DBN	All infrastructure	No
[63]	Assess system resilience across absorption, adaptation, and recovery phases	No	Agent based modelling	SCADA and SUC	Yes (Physical)
[59]	Model responses to disruptions considering interdependencies, failure propagation, and optimal resource deployment	Yes	Dynamic Network flow	Electricity and Metro network	Yes

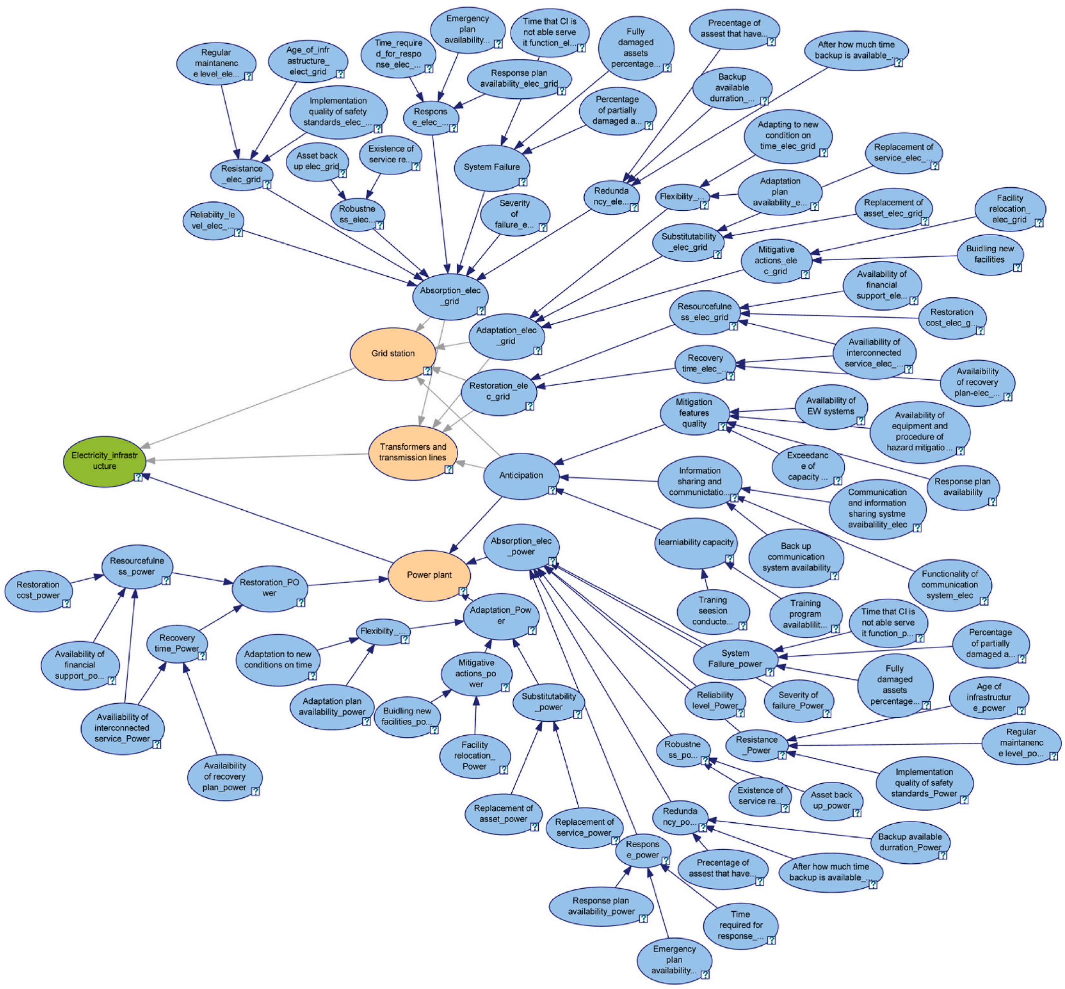

Fig. A. 1. Bayesian network structure for electricity infrastructure sector.

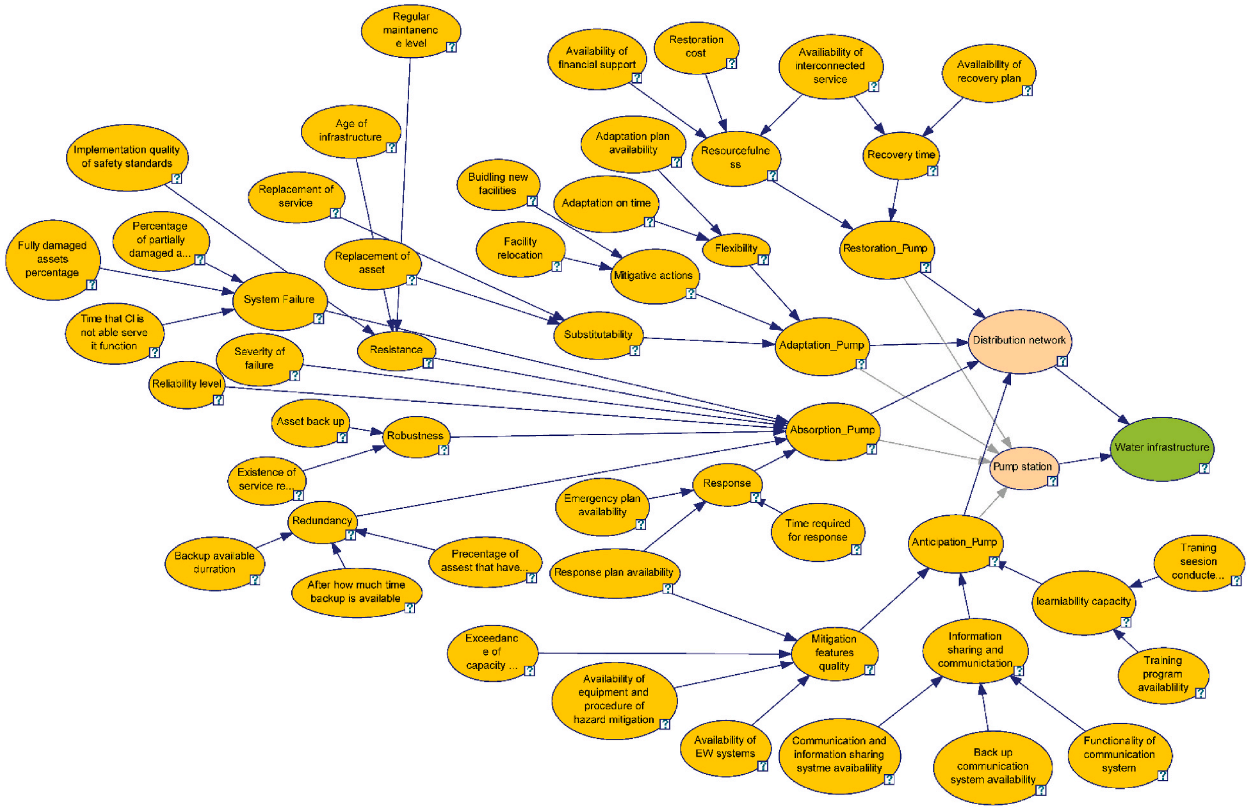

Fig. A. 2. Bayesian network structure for water infrastructure sector.

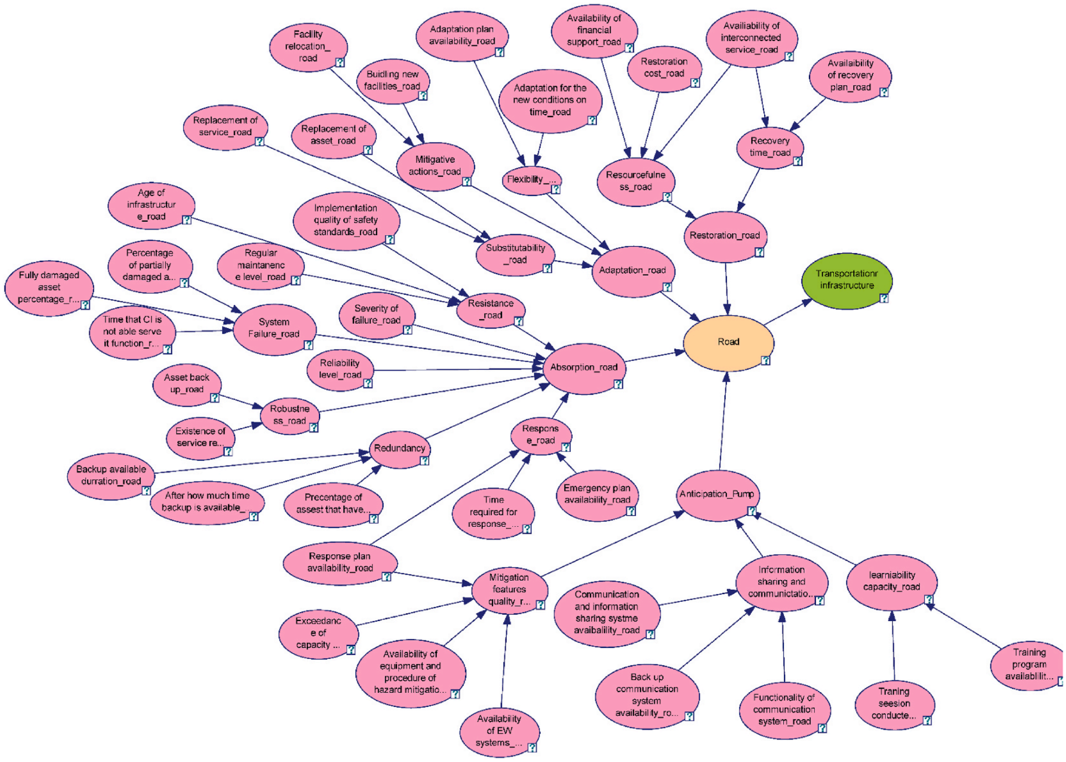

Fig. A. 3. Bayesian network structure for transportation infrastructure sector.

Table A 3Chi-Square test results for variation in model prediction vs expert judgement.

		Variation in model predicted values															
		Pump station and distribution network				Road infrastructure				Transformers and Grid stations				Power plant			
	F_0	Decrement	No change	Increment	Total	Decrement	No change	Increment	Total	Decrement	No change	Increment	Total	Decrement	No change	Increment	Total
Variation in expert judgement	Decrement	4	5	3	12	5	6	6	17	8	6	5	19	13	7	4	24
	No change	1	10	4	15	5	21	5	31	5	11	7	23	4	6	3	13
	Increment	3	6	34	43	5	8	9	22	4	13	11	28	3	11	19	33
	total	8	21	41	70	15	35	20	70	17	30	23	70	20	24	26	70
	fe																
	Decrement	1.37	3.60	7.03	12.00	2.57	6.00	3.43	12	2.91	5.14	3.94	12	3.43	4.11	4.46	12
	No change	1.71	4.50	8.79	15.00	3.21	7.50	4.29	15	3.64	6.43	4.93	15	4.29	5.14	5.57	15
	Increment	4.91	12.90	25.19	43.00	9.21	21.50	12.29	43	10.44	18.43	14.13	43	12.29	14.74	15.97	43
	Total	8.00	21.00	41.00	70.00	15	35	20	70	17	30	23	70	20	24	26	70
	X^2																
	Decrement	5.04	0.54	2.31	7.89	2.29	0.00	1.93	4.22	8.88	0.14	0.28	9.30	26.72	2.02	0.05	28.79
	No change	0.30	6.72	2.61	9.63	0.99	24.30	0.12	25.41	0.51	3.25	0.87	4.63	0.02	0.14	1.19	1.35
	Increment	0.75	3.69	3.08	7.52	1.93	8.48	0.88	11.28	3.98	1.60	0.69	6.27	7.02	0.95	0.57	8.54
	Total	6.08	10.96	8.00	25.04	5.21	32.78	2.93	40.92	13.36	4.99	1.85	20.20	33.76	3.12	1.81	38.68
Odds ratio		**1.6**		**9.44**		**1.33**		**1.13**		**4.33**		**1.02**		**6.81**		**3.02**	

Appendix B. Dynamic Bayesian Network

In the proposed methodology, a Bayesian Network (BN) is used to model the CI system. A BN is depicted as a directed acyclic graph, which comprises nodes and directed arcs. In this graph, nodes represent variables, and directed arcs indicate the dependencies between these variables through conditional probabilities. The arcs flow from parent nodes to child nodes. Marginal probabilities are assigned to root nodes, which have no parent nodes [50,51,70,71]. Conditional probabilities are assigned to all other nodes. Once the marginal and conditional probabilities are determined, the joint probability of nodes is calculated based on the topology of the BN.

Let $X = \{X_1, X_2, \dots \dots, X_i, X_{i+1}, \dots\dots\dots\dots, X_q\}$ be the series of nodes in the BN; then joint probability of the outcome variable, X can be written as in Equation (4),

$$P(X) = \prod_{i=1}^{q} P(X_i | Pa(X_i)) \tag{4}$$

Pa (X_i) = set of parent nodes of variable X_i.

Furthermore, BN facilitate the adjustment of initial probabilities as new evidence is obtained, a procedure known as posterior analysis. This feature permits BNs to integrate new evidence by employing Bayes' theorem. The posterior probability P(X|E), given the new evidence E, is determined through Equation (5).

$$P(X|E) = \frac{P(X,E)}{P(E)} = \frac{P(X,E)}{\sum_x P(X,E)} \tag{5}$$

BNs have the capacity to include several states for nodes and consider failures caused by common factors through causal connections between nodes. BNs can also forecast and adjust event probabilities with the emergence of new evidence. These capabilities make BNs more adaptable and relevant compared to conventional risk assessment techniques [55,61]. Consequently, they excel in evaluating causation, and assessing the impact of various options under uncertain conditions, making them well-suited for interdependency modeling [51,71,77]. Notably, BNs offer a distinct advantage of effectively handling uncertainties associated with data, as they furnish a unified framework capable of accommodating disparate data types—ranging from expert surveys and field measurements to simulation data and facilitating data updates across various stages [70,71,74,75,77,87].

Employing BNs for interdependency modelling may encounter two primary limitations. Firstly, BNs typically rely on discretised variables rather than continuous variables, which differs from the continuous nature often encountered in practical applications. To address this constraint, DBN is used, which can handle both discrete and continuous variables, in addition to temporal factors [47,50,51,69–72,74,75]. A DBN, an extension of BN, a series of variables is linked over a discretised timeline, taking into account the temporal changes in the probabilities assigned to these variables [47,71,72,74,75]. Within a DBN model, a node at time t is impacted by both its parent nodes at time t and its own states, as well as parent nodes, from the previous time step. The DBN structure includes two types of arcs: a) regular arcs, linking nodes within the same time frame, and b) temporal arcs, connecting nodes across various time frames. Mathematically, the joint probability of a series of variables is expressed using Equation (6):

$$P(X^t) = P\left(X_1^t, X_2^t, X_3^t, \ldots\ldots\ldots\ldots\ldots, X_q^t\right) = \prod_{i=1}^{q} P\left(X_i^t \middle| X_i^{t-1}, Pa\left(X_i^t\right), Pa\left(X_i^{t-1}\right), Pa\left(X_i^{t-2}\right), \ldots.., Pa\left(X_i^0\right)\right) \tag{6}$$

$Pa(X_i^t)$ = parent nodes of variable X_i at time t.

Appendix C. Methodology for data collection

Case study data was collected through an expert survey. Therefore, the sampling was conducted using nonprobability sampling techniques [88,89]. This is further explained by Keeney et al., who state that heterogeneous sampling (purposive sampling) is used for expert judgment [88,90,91]. For homogeneous groups, a sample size of 10–15 is generally deemed adequate [92,93]. Therefore, this study leveraged the expertise of 10–12 panelists from each infrastructure sector to obtain the data needed for the analysis. The selected panelists included professionals in the fields of infrastructure planning, design, construction, and maintenance from the respective organizations. When selecting the panel members, their experience in the infrastructure sector, education level, and their ability to understand the research objectives were considered. Each member had a minimum of 5 years of working experience in their respective infrastructure sector in Sri Lanka. All panel members had bachelor's degrees in engineering, and 25 out of the 34 members had pursued postgraduate degrees. The experts were chosen based on their professional experience. Accordingly, 12, 12, and 10 experts were selected from the transportation, water, and electricity sectors, respectively. Among the experts selected from the water infrastructure sector, four hold a PhD in civil engineering, while six hold postgraduate qualifications. In the electrical infrastructure, two experts hold a PhD in Electrical Engineering, while five have postgraduate qualifications. In the road infrastructure sector, four experts hold a PhD in civil engineering, while five hold postgraduate qualifications.

Furthermore, these experts comprise 3 assistant general managers, 12 planning engineers, 13 civil engineers, and 6 electrical engineers. The work experience of the experts is presented in Table C 1.

Two questionnaires were developed to gather expert judgments in the modeling exercise. One questionnaire was designed to determine the indicators and importance weights for each indicator. Another questionnaire was developed to identify the major assets, facilities, and infrastructures belonging to the selected CIs, assess interdependencies, and measure each indicator.

Table C 1Working experience of the experts.

Working experience (x) in years	Number of experts		
	Transportation	Water	Electricity
x < 15	0	0	0
15 ≤ x < 20	2	3	2
20 ≤ x < 25	3	4	2
25 ≤ x < 30	5	3	4
30 ≤ x	2	2	2
Total	12	12	10

Appendix D. CPTs of the node representing the main indicators and capacities

Table D 1CPTs of the node representing the main indicators and capacities.

Capacities/Main Indicators (Child node)	Main Indicator/Sub indicators (Parent node)	Road infrastructure	Transmission and Transformers and grid stations	Power plant	Pump station and water distribution network
Anticipative	Quality of mitigation features	0.39			
	Information sharing and communication	0.41			
	Learnability and training capacity	0.2			
Absorption	System failure	0.08			
	Severity of failure	0.07			
	Reliability of asset	0.19			
	Resistance	0.17			

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(*continued*)

Capacities/Main Indicators (Child node)	Main Indicator/Sub indicators (Parent node)	Road infrastructure	Transmission and Transformers and grid stations	Power plant	Pump station and water distribution network
	Robustness	0.21			
	Redundancy	0.23			
	Response	0.05			
Restoration	Recovery time	0.22			
	Resourcefulness	0.78			
Adaptation	Substitutability	0.65			
	Flexibility	0.11			
	Mitigative actions	0.24			
Quality/extent of mitigating features	Availability of equipment and procedure for the hazard mitigation	0.57	0.24		0.57
	Availability of EW systems	0.12	0.14		0.12
	Exceedance of capacity demands	0.15	0.17		0.15
	Availability of response plans	0.16	0.45		0.16
Information sharing and communication system	Availability of communication and information sharing system	0.67	0.67		0.67
	Functionality of the communication system	0.12	0.12		0.12
	Availability of backup communication system	0.21	0.21		0.21
Learnability/Training capacity	Existence of the training system	0.17	0.17		0.17
	Number of training session conducted for months	0.83	0.83		0.83
System failure	Percentage of fully damaged assets (Beyond the repairability)	0.45	0.45	0.45	0.64
	Percentage of partially damaged assets	0.45	0.4	0.45	0.21
	Time that CI is not able serve it's intended function	0.1	0.15	0.1	0.15
Resistance	Ages of Infrastructure	0.35	0.12	0.34	0.72
	Implementation quality of safety standards	0.3	0.14	0.19	0.12
	Level of regular Maintenance	0.35	0.74	0.47	0.16
Robustness	Asset back up	0.64	0.86	0.53	0.82
	Existence of the service replacement	0.36	0.14	0.47	0.18
Redundancy	Percentage of assets that have backup.	0.51	0.74		0.4
	How long backup is available	0.32	0.12		
	After how much time backup is available	0.16	0.14		0.4
Response	Availability of response plan within infrastructure/assets	0.46	0.34	0.46	0.2
	Time needed to response	0.07	0.24	0.07	0.13
	Emergency plans within assets	0.47	0.42	0.47	0.12
Recovery time	Availability of special recovery plan	0.5	0.85	0.41	0.75
	Availability of interconnected assets	0.5	0.15	0.59	0.73
Resourcefulness	Availability of interconnected assets	0.45	0.18	0.32	0.27
	Availability of financial support	0.45	0.24	0.45	0.18
	Restoration cost	0.1	0.58	0.25	0.24
Substitutability	Possibility of the replacement of asset	0.5	0.58	0.54	0.58
	Possibility of the replacement of Service	0.5	0.42	0.46	0.42
Flexibility	Availability of adaptation plan	0.21	0.78	0.12	0.5
	Adaptation for new conditions on time	0.79	0.22	0.88	0.5
Mitigative actions	Facility relocation	0.41	0.87	0.5	0.87
	Building new facilities	0.59	0.13	0.5	0.13

Data availability

The data that has been used is confidential.

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